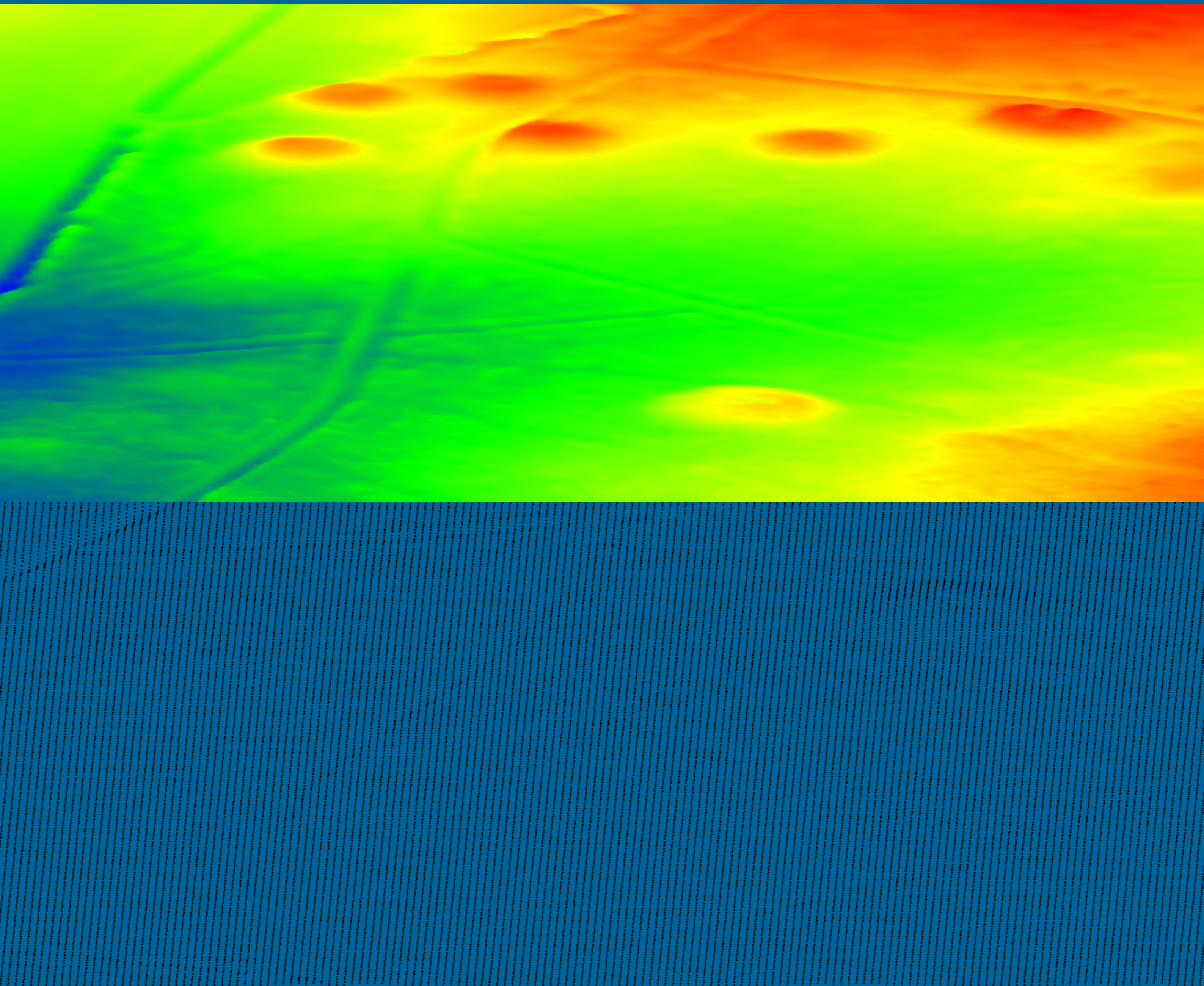

LIDAR based semi-automatic pattern recognition within an archaeological landscape

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LIDAR based semi-automatic pattern recognition within an archaeological landscape

Inauguraldissertation zur Erlangung der Doktorwürde der Philosophischen Fakultät der Universität Heidelberg

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FORMALITIES

This dissertation finalizes a structured graduate program at the Interdisciplinary Center for Scientific Computing in collaboration with the Junior Research Group, Digital Humanities, at the Cluster of Excellence, Asia and Europe in a Global Context. The dissertation *LIDAR based semi-automatic pattern recognition within an archaeological landscape* is written as a monograph at the Institute of Ur- und Frühgeschichte und Vorderasiatische Archäologie, Faculty of Philosophy, Heidelberg University.

The projects first supervisor is Dr. Armin Volkmann, Junior Research Group leader, Cluster of Excellence, Asia and Europe in a Global Context, Heidelberg University. The second supervisor is Prof. Dr. Thomas Meier, Institute of Ur- und Frühgeschichte und Vorderasiatische Archäologie, Heidelberg University.

The project was also aided by the two mentors of Prof. Dr. Bernhard Höfle, Geographisches Institut Heidelberg, Heidelberg University, and Prof. Dr. Diamantis Panagiotopoulos, Institute of Klassische Archäologie, Heidelberg University.

In connection with the dissertation, three publications have been produced. Two publications are as first author, and one as co-author. Several other means of public mediation have also been carried out during the project, such as presentations of results at conferences, posters, blogs, and smaller technical and practical publications. The three main articles produced are published.

I. Pfeiffer, M., K. Raun & A. Volkmann. 2016. Digital Mapping – Detection and prospection through digital and physical landscapes at Koumasa, Crete. *HeiDOK:* Heidelberg dokumentenserver, Heidelberg. DOI: 10.11588/heidok.00021948

II. Raun, K., M. Pfeiffer & B. Höfle. 2018. Visual detection and interpretation of cultural remnants on the Königstuhl hillside in Heidelberg using airborne and terrestrial LIDAR data. In: *Digital Geoarchaeology*. New Techniques for Interdisciplinary Human-Environmental Research. Eds. C. Siart, M. Forbiger & O. Bubenzer. Natural Science in Archaeology, Springer International Publishing, AG 2018, p. 201-12. DOI: 10.1007/978-3-319-25316-9_13

III. Raun, K. & D. Paterson. 2019. Systematic literature review on automated monument detection. In: *Proceedings of the 44th conference on computer applications and quantitative methods in archaeology*, Oslo, March 2016, CAA Norway.

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This thesis is the outcome of work and research in between 2014 and 2018 at the Institute of Ur- und Frühgeschichte und Vorderasiatische Archäologie, Faculty of Philosophy, Heidelberg University. The project is also an outcome of collaboration by the Interdisciplinary Center for Scientific Computing, IWR, and the Cluster of Excellence, Asia and Europe in a global context.

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Lastly, the most heartfelt thanks goes to my wife, Trine Kellberg Nielsen, who have been the sole reason why I embarked on this adventure, and who during this whole project have kept supporting and aiding me in the process.

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Term & Abb.	Description
absolute accuracy	A measure that accounts for all systematic and random errors in a data set
accuracy	The closeness of an estimated value to a standard or accepted value of a particular quantity
ALS	Airborne Laser Scanning
amplitude	range: wave extent of emitted pulse from mean
ANN	Artificial Neural Network
AoI	Area of Interest
Aperture angle	Laser scanner angle from origin
ASPRS	American Society for Photogrammetry and Remote Sensing
Azi	Azimuth: angular perspective of illumination, i.e. Digital celestial sun in LIDAR data
BIL	Band interleaved by line: Compression file for multiband image data
BIP	Band interleaved by pixel: Compression file for multiband image data
BLV	Bayerisches Landesamt für Vermessung
BM	Burial Mound
BSQ	Band sequential: Compression file for multiband image data
BVV	Bayerisches Vermessungsverwaltung
cm	centimeter
confidence level	accuracy: The percentage of points within a data set that are estimated to meet the stated accuracy
Crowd-sourced	Gaining information and services from relatively groups to aid a cause or purpose to produce cumulative results
DEM	Digital Elevation Model
digital truth	Observed digital evidence: non-calibrated with ground truth
DSM	Digital Surface Model
DTM	Digital Terrain Model
Echo	Backscattered power of the return signal
EDA	Exploratory Data Analysis
first pulse	return pulse of the highest feature: maximum
Full waveform	Detected and digitized backscattered energy of the receiving unit allocated to one observation
FW	Full waveform
GeoTIFF	Georeferenced Tagged Image File Format
GIS	Geographic Information System
GPS	Global Positioning System
ground truth	Observed evidence: often by survey
Hz	Hertz
IMU	Inertial Measurement Unit
intensity	Strength of light return signal
ISPRS	International Society for Photogrammetry and Remote Sensing
k-d tree	Binary tree for k-dimensional representation of data structure by splitting half-spaces
***k*-means**	Partition of n observations by mean
***k*-means**	Partition of n observations into k-clusters

clustering	
kurtosis	The measure of relative “peakedness” or flatness of a distribution
LAS	Standardized binary file format for laser scanning data
Laser	Light Amplification by Stimulated Emission of Radiation
last pulse	return pulse of the lowest feature: minimum
LIDAR	Light Detection And Ranging; Light RADAR
LRM	Local Relief Model
LRM	Local Relief Model
LS	Laser Scanning
m	meter
mean error	The average error in a set of values, obtained by adding all errors, e.g. in x, y or z, and then dividing by the total number of errors for that dimension
measurement error	Difference between the theoretically-unknowable “true” value of a parameter and its measured value
MLS	Mobile Laser Scanning
mm	millimeter
MSII	Multi-Scale Integral Invariants
n	unspecified iterations
NA	Network Analysis
nm	nanometers
NN	Neural Network
NSSDA	National Standard for Spatial Data Accuracy
PCA	Principal Component Analysis
pixel	the smallest physical point in a raster
ppsm	points per square meter
precision	The closeness with which measurements agree with each other, even though they may all contain a systematic bias.
PS	Phase-Shift
pts/m2	points per square meter
p-value	Probability value of a given statistical model to measure statistical significance
resolution	The smallest unit a sensor can detect or the smallest unit an orthoimage depicts
S	Sample standard deviation. Calculated as: $sx=\sqrt{\frac{1}{(n-1)}\sum_{i=1}^{n}(x_i-\bar{x})^2}$
skew	A measure of symmetry or asymmetry within a data set. Symmetric data will have skewness towards zero
SLR	Systematic Literature Review
smc	simple matching coefficient
standard deviation	A measure of spread or dispersion of a sample of errors around the sample mean error
SVF	Sky-View Factor
systematic error	An error whose algebraic sign and, to some extent, magnitude bears a fixed relation to some condition or set of conditions
template	standardized or idealized data
TIFF	Tagged Image File Format
TIN	Triangulated Irregular Network
TLS	Terrestrial Laser Scanning
TOF	Time-of-Flight

Trained Data	Data process where rules and variables increase to improve output, i.e. learn by dataset. Untrained data is output by one rule or criteria.
uncertainty	also a parameter to characterize the dispersion of confidence value
USGS	United States Geological Survey
vector	vector graphics of entities through point, line or polygon geometry
XYZ	3dimensional coordinate structure
XYZI	4dimensional coordinate structure with intensity recording
µm	micrometers (1 µm = 1000 nm)

1. INTRODUCTION

Within the framework of this thesis, the main objective is to investigate and assess the status of LIDAR based semi-automatic pattern recognition within an archaeological landscape. This implies not only semi-automatic detection and information extraction of archaeological monuments within digital landscapes, but also assessment and development of the field. This will be done to determine impact and potential within the archaeological community for automating procedures towards improved possibilities of detection and management of cultural heritage in the landscape.

LIDAR data provides a novel approach for locating and monitoring cultural heritage in the landscape, especially in areas of logistical complications, e.g. forest, rough terrain, and remote areas. Manuel detection and mapping of archaeological information in the landscape is a time-consuming task. To improve and increase the possibilities of cultural heritage detection and management, computational means can offer a solution, and even reveal details that are not possible to detect with the naked eye. However, to implement automated information extraction from LIDAR data, different stages of standardized workflows are necessary for archaeological use of LIDAR data. Presently the use of LIDAR within the archaeological community often lacks standardized approaches for proper handling, developing, and processing for cultural heritage detection and management. Further, the majority of stakeholders within the field of archaeology and cultural heritage management encounter various problems regarding macro- and micromanagement when handling and processing LIDAR data, repeatedly resulting in quantitative assessment being impractical or impossible. Thus, In order for LIDAR data to become a truly competent method for heritage management, a large-scale quantitative approach for handling, developing, and processing needs to be formed and defined. For this, the effort of this project will be focused on quantitative methods for handling and processing LIDAR data and digital landscapes by systematic and semi-automated approaches. The aim of this project is the creation of a large-scale approach for a wide array of scientific fields and application domains within archaeology, informatics, and the earth sciences. However, the project will have particular emphasis on archaeological monuments within LIDAR based digital landscapes. Archaeological monuments are in this context defined as features of the past that have become part of the landscape as covered or partly covered structures. Monuments are defined as physical entities with a physical presence in the landscape. They consist of a wide variety from singular entities to multiple entities in complexes. Monuments in general do not imply temporal definition, but archaeological monuments imply a temporal scope towards the past and something not of contemporary use by original intention. This implies that archaeological monuments refer to features and structures that were once or are still forgotten, hidden or partly hidden in the landscape. A process in which archaeological monuments have become assimilated and earthbound with the landscape through wear and tear by time, and by external and internal decomposition of materials covering or partly covering the structures and features of interest. As a result, archaeological monuments co-exist in LIDAR data as elusive patterns part of the modern landscape and of the terrain. This complicates the possibility of manual distinction out in the field, as well as digitally by remotely sensed data such as LIDAR. However, by learning the variables and patterns of archaeological monuments, it is possible to learn how to distinguish the structures by human visual inspection as well as by computational semi-automated detection. This necessitates that we understand the patterns within our digital landscapes of LIDAR data created by automation and semi-automation. All computational means can be automated procedures: from pre-processing, to processing, and post-processing. By any human interaction, however, the process becomes semi-automatic. Thus, the algorithmic procedures can be automated to a point of validation and interpretation, but then becomes semi-automatic investigation. The question therefore becomes, is it possible to completely automate investigation of the landscape of the past from automated segmentation to fully automated classification of landscape? This will be investigated and answered in this thesis, but also with a notion of quality of information compared to cost and use. Meaning, any approach of computation, has to be compared to human gain of understanding. Naturally, this is not answered by a simple 'yes' or 'no' to the improvement of archaeological data and information, and not something that can be confidently located on a binary scale between 1 and 0. However, it is on a scale. On a scale that is constantly moving and changing position in space towards 1 or 0 as we progress and improve our understanding of the possibilities to quantify and extract information for archaeological mapping in the analog and digital landscape. Because, the potential is not yet defined, but we can see the trajectory currently set in motion.

1.1 MOTIVATION

Within an archaeological scope, the motivation for this thesis is to asses LIDAR data for automated and semi-automated procedures for the detection of archaeological patterns and monuments in digital landscapes. This will be done by applying simple and open algorithmic means of visualization, segmentation and classification in and of digital LIDAR landscapes towards large-scale archaeological monument detection. In order to do so, the thesis will give a thorough account of the archaeological use and potential of LIDAR data; qualitative and quantitatively define the state and development of the field for automatic and semi-automatic archaeological detection by LIDAR data;

indicate best practice and state of the art; exemplify quality of detection by automated and semi-automated segmentation and classification of data; indicate range of potential application; apply template matching for large-scale cultural heritage investigation; compare human versus computational detection; and lastly discuss and stipulate potentials within the field of LIDAR based pattern recognition. The main objectives and research questions are focused on applicability by potential use through time and cost efficiency, and more importantly so, the quality of extracted information from LIDAR data. The objectives and research questions can consequently be defined by use and potential use within the archaeological community. This is aimed towards creating large-scale digital landscape investigations to be more generally and more effectively applied within the archaeological community. These perspectives are formulated into four questions to exemplify the scope of the thesis:

What is LIDAR and how is it used within archaeology?

To what degree is the application of automated and semi-automated procedures applied for the detection of archaeological monuments within the archaeological community?

Can we perform LIDAR based semi-automatic large-scale investigations of landscape by open and simple segmentation and classification?

Are the results of segmentation and classification improving detection and management of archaeological monuments in LIDAR landscapes?

1.2 CHAPTERS

To answer the research questions above, the thesis structure follows the same outline by investigating data, community, application, and impact. This compresses into five main chapters with subsections following the general guideline.

Chapter 2: ARCHAEOLOGICAL LIDAR

Chapter 3: LANDSCAPE PERSPECTIVES

Chapter 4: STATE OF AUTOMATED AND SEMI-AUTOMATED DETECTION WITHIN REMOTE SENSING ARCHAEOLOGY

Chapter 5: APPLIED DETECTION IN LIDAR DATA

Chapter 6: CONCLUSIONS AND PERSPECTIVES

Chapter 2 explains the use of LIDAR data, the implementation in archaeological practice, as well as outline limitation and potential of using LIDAR in archaeology. **Chapter 3** establishes an introduction to LIDAR data from Lower Franconia further investigated in chapter 5, as well as constructing interpretation of landscape perspectives. **Chapter 4** defines the field of automated archaeological monument detection by a systematic review to qualitative and quantitative assess state of the field by development and evolution, as well as propose state of the art and best practice within archaeology and beyond. Key focus will be on the degree of application for cultural heritage management and information extraction. **Chapter 5** will elaborate and apply detection algorithms for model and data driven approaches of automatic and semi-automatic information extraction. Chapter 5 will also analyze the results and qualitatively and quantitatively evaluate the difference between human versus computational interpretation of landscape. **Chapter 6** will discuss the results gathered from chapter 2-4 to conclude and determine the future of automated and semi-automatic archaeological information extraction and monument detection.

1.3 CREDIT

Gratitude is extended towards the Bavarian State Offices for Sites and Monuments (Bayerisches Landesamt für Denkmalpflege) and the Environment (Bayerisches Landesamt für Umwelt) for providing site information, together with a particularly thanks to the Bavarian State Office for Surveying and Geoinformation (Bayerisches Landesamt für Vermessung und Geoinformation) for providing access to unpublished LIDAR point clouds for the area of Unterfranken. Gratitude also has to the *Heidelberg Graduate School of Mathematical and Computational Methods for the Sciences*, HGS MathComp, at the *Interdisciplinary Research Center for Scientific Computing,* IWR, for funding and aid. Assistance and thanks also go to the *Junior Research Group Digital Humanities* at the *Cluster of Excellence, Asia and Europe in a Global Context*, as well as the Institute of Prehistory, Protohistory, and Near-Eastern Archaeology, Faculty of Philosophy, Heidelberg University.

2. ARCHAEOLOGICAL LIDAR

The increasing amount of landscape modification by stakeholders has necessitated innovation and cost-effective methods for archaeologist to effectively keep up with the growing pressure on cultural heritage in and on the landscape. One of the means for improving archaeological surveying, monitoring, and documenting cultural heritage in the landscape, has been given in the shape of Airborne Laser Scanning, also referred to as LIDAR (Crutchley & Crow 2009). The presences of LIDAR in archaeological studies have been increasing in the last two decades (see also chapter 4). This is especially true within Europe due to regional and nationwide scanning campaigns for improved knowledge on the physical landscape surrounding us for administrative and inquisitive purposes (Doneus & Kühteiber 2013, 32). This, in return, has given archaeologist a perfect window for complex site understanding and landscape investigations by the increased availability of remotely sensed data. Region and nationwide documentation by laser scanning have also given way to a wide array of scientific projects concerned with standardized and systematic documentation of cultural heritage within the landscape (e.g. Bofinger & Hesse 2011; De Laet et al. 2007; Doneus et al. 2006; Schmidt et al. 2005; Schneider et al. 2015; Trier & Zortea 2012). To understand the impact of LIDAR in archaeology, it is first important to understand what LIDAR is and the potential impact on archaeological mapping, documentation, and management. This chapter will define the layout of LIDAR data to understand the potential application of archaeological LIDAR for information extraction and detection of archaeological monuments in the landscape.

2.1 REMOTE SENSING

The use of remote sensing has and is changing archaeological practice of analysis, detection, and management of cultural heritage in the landscape. From the mid-19th century and onwards, the presence of remotely sensed data has evolved towards a spearhead praxis within archaeology. Especially in the aftermath of the First World War, aerial reconnaissance and documentation grew in importance (Cowley et al. 2010; Olesen et al. 2011, 8-9). The early oblique and ortho images captured from low-flying airplanes were originally meant for mapping, but have since highly impacted the field of archaeology. The practice of remote documentation of crop marks, monuments, earthworks and cultural landscapes, is still one of the most applied approaches within large-scale archaeological reconnaissance and management (Cowley et al. 2010; Olesen et al. 2011; Olesen & Klinkby 2012; Verhoeven 2009). Data from satellite imagery has likewise increased the dimensionality of past and present landscape by untargeted documentation used as supplementary information within archaeology (e.g. De Laet et al. 2007; Figorito & Tarantino 2014; Hesse 2015) or main documentation (e.g. Grøn et al. 2003; Lambers & Zingman 2012; Siart et al. 2008). Analyzing crops and subsurface differentiation in hyperspectral images can provide unique proxy values for understanding in-situ cultural heritage in the landscape (Cavalli et al. 2013; Custer et al. 1986; Doneus et al. 2014). Similar to aerial raster, LIDAR data provides remote data to understand landscape, whether by terrestrial or aerial documentation. Currently, LIDAR data enhances our knowledge of landscape in a comparable manner to early oblique and ortho images by giving new perspectives and means to improve knowledge of cultural landscapes (Opits & Cowley 2013).

Understanding cultural landscape requires both data analysis and correlation with other sources of remotely sensed data. In performing comprehensive large-scale studies and repeated site management, many of the individual procedures of remotely sensed documentation becomes time consuming. Consequently such tasks become peripheral due to the lack of public sensation value, and subsequently funding. Many of the repeated tasks of processing large-scale remotely sensed data, are, as a consequence, becoming automated computational or semi-automatic procedures. Examples of such are; automated georeferencing (e.g. Verhoeven et al. 2012), automated site detection (e.g. Menze & Ur 2012; Trier & Zortea 2012; Schneider et al. 2015), and machine learning towards automatic analysis and feature learning (e.g. Arel et al. 2010; Belgiu et al. 2014; Maaten et al. 2007; Trier et al. 2016). Automated detection and analysis within cultural landscapes is not a particular new field within archaeology (e.g. Lemmens et al. 1993; Redfern 1997). However, the development of automated monument detection has been evolving for a long time without much of an impact. However, these former tendencies are changing, and automated segmentation and classification are becoming necessary to cope with the vast amount of remotely sensed data and cultural heritage information.

2.2 BASIC LIDAR

As of yet, no consensus exist on how to coin LIDAR, and is therefore used by different terms and concepts. The most common reference of LIDAR in papers goes by the assumption of LIDAR as an acronym change from RADAR, *Radio Detection and Ranging*, to *Light Detection and Ranging*. The acronym for LIDAR as *Light Detection and Ranging,* is one of the most used means of understanding LIDAR, but is not necessarily depicting the correct term for the technique. LIDAR is also referred to as LADAR, *Laser Detection and Ranging, Laser Radar* (Geist et al. 2009, 311), as well as coined by the linguistic blend of “light radar” (Ring 1963) supported by the Oxford English Dictionary. The capitalization of letters within LIDAR also changes in relation to perception of origin and meaning.

Thus LIDAR can be spelled: LIDAR, LiDAR, LIDaR, LiDaR, LIdar, Lidar or lidar. For this thesis, a standard has been integrated based on the United States Geological Survey, *USGS,* standard for description of Laser Scanning by LIDAR principles. The USGS together with the *American Society for Photogrammetry and Remote Sensing, ASPRS,* and *International Society for Photogrammetry and Remote Sensing, ISPRS*, has a long history of working towards standards for LIDAR data and metadata (Heidemann 2012; ASPRS 2013). The USGS and SPRS use the two derivatives: LIDAR & lidar. The standard from the *International Organization of Standardization*, ISO, is lidar as Light Detection and Ranging, for documenting and specifying LIDAR scanning (ISO TS 19139-2 2014) . The standard used within this thesis will therefore be LIDAR, as it does not imply anything regarding origin by capitalization, and thus simply implies a difference between LIDAR and LASER as scale. However, by definition LIDAR scanning is Laser Scanning from air and land, but is for many fields mostly associated with airborne scanning due to the capabilities of large-scale coverage of landscape. Airborne Laser Scanning (ALS) and Terrestrial Laser Scanning (TLS) are therefore more generic terms of LIDAR scanning. LIDAR is Laser Scanning (LS), and LASER is an acronym for *Light Amplification by Stimulated Emission of Radiation* (Gould 1959). LIDAR scanning works similar to total station measurements, but is differentiated by large-scale random light emission versus controlled measurement, e.g. a total station. The technical measurements of points work on similar principles of triangulation to determine position in space, but with difference of travel time calculation between emitted and received pulse. It can therefore be argued that a better term for LIDAR scanning is Laser Scanning (LS), differentiated by terrestrial (TLS), mobile (MLS), and airborne (ALS) platforms. There is, however, a use for the differentiation of terms from LIDAR to Laser Scanning, and that is reflected in scale and resolution. With the increasing use of 3D models from objects and landscape, the term Laser Scanning can be argued to be more commonly accepted as artefact and object scanning, whereas the term LIDAR is more often used for large-scale investigations. Thus Laser Scanning by LIDAR highlights a specific use compared to other applications of Laser Scanning, and consequently helps a term definition of scale. The term use of LIDAR is then used as an overarching definition for the field of large-scale Laser Scanning. The terms for ALS, MLS, and TLS will be used when necessary to mark difference based on airborne, terrestrial or mobile mounting. LIDAR, despite the intention of the term, in the end similar to the RADAR principle by using infrared and near infrared light instead of emitting radio waves to detect particles and physical conditions.

2.3 THE LIDAR POINT

The LIDAR point is in the end the LIDAR product. The basic LIDAR point is three sets of values to construct a coordinate transformed to a Cartesian plane. The raw LIDAR point is an active emitted pulse, generally at a single near-infrared wavelength. The backscattered pulse is reflected in the same narrow wavelength of imaging spectrum. The reflected backscattered repetition pulse is registered based on intensity, which provides a possibility of understanding terrain or canopies by the intensity of reflection. Most laser scanners record the intensity, resulting in LIDAR data having reflection intensity, or echo, recorded in the point as: XYZI. This also provides, that the digital footprint of the point cloud can be used to segment and classify based on reflected intensity. However, the digital footprint based on intensity of the echo is a rough definition of surface or object qualities, leading it to be more relevant for segmentation then classification. This is exemplified in the schematic of Figure 1. Thus by using the full waveform of the amplitude, it can be possible to distinguish more details, but especially for archaeological mapping the discrete last return of direct energy recording is the most relevant.

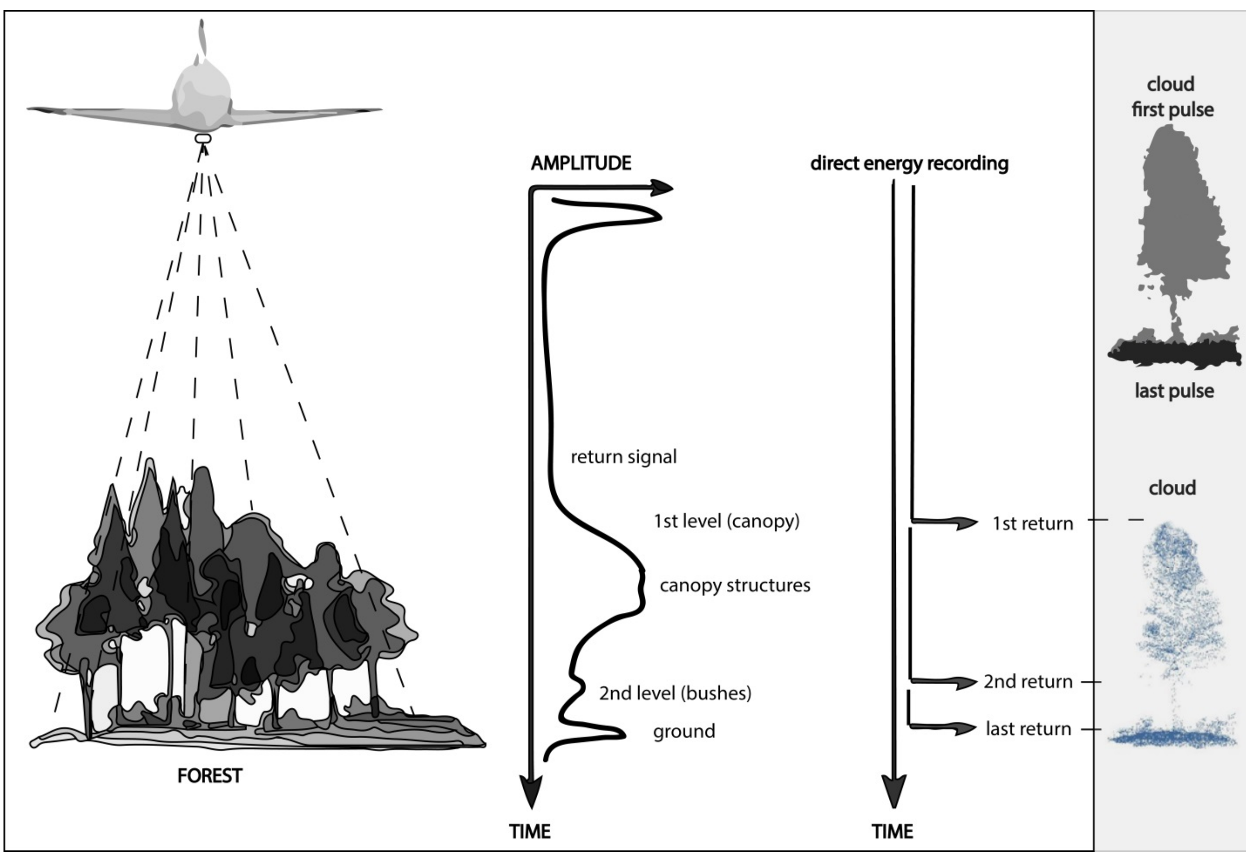

FIGURE 1: AIRBORNE LIDAR RECORDING BY COMPARISON OF FULL WAVEFORM IN THE AMPLITUDE OR DISCRETE SCANNING BY DIRECT ENERGY RECORDING

Typically, LIDAR for archaeological use is delivered and used by the simple segmentation of first and last return of the pulse, because the main concern of archaeological mapping is not the surface, but rather the terrain by its inclusion and assimilation of traces and patterns of the past. Nonetheless, understanding the reflection value gives opportunities to manipulate the scanned surface based on more criteria than spatial composition, and thus resulting in an added dimension for understanding the landscape. Examples of such can be seen by the results of Challis et al. 2011, by the potential of archaeological and geological crop mark detection based on ALS intensity data. Intensity values can also be used to understand density or biomass as a proxy for the detection of archaeological features (e.g. Briese et al. 2014; Stott et al. 2015). However, the individual LIDAR point does not provide much information, but by the combined structure of the point cloud, it provides contextual surface information from which information can be understood. Typically, archaeological LIDAR is used by its segmentation between first and last pulse, with the surface model containing all first pulses, and the terrain model containing first pulse, unless last pulse is registered. However, as previously mentioned, this does not provide a complete terrain model, meaning additional filters needs to be applied to remove structures that are not part of the scanned present natural landscape (Belgiu et al. 2014; Silthole 2005). This is especially necessary for airborne LIDAR that produces huge datasets. An airborne laser scanner emits pulses at extreme rates from which huge point clouds are created of the landscape. So far, the limit of sampling rate is not yet determined, and the question is not whether LIDAR resolution can be improved, but rather whether what resolution is needed and what is optimal for landscape studies. The sampling rate is determined by hertz and amount of channels used for measurement rate, making airborne scanners produce point clouds anywhere between thousands to millions of points per second. Thus, the potential of archaeological LIDAR is defined by available *point per square meter,* ppsm, and point density to a distance needed to visualize data to a desired degree of detail. An increase in amount of ppsm naturally leaves restrains on computation by file size through density or scale. However, archaeological LIDAR is often delivered as values of first and last pulse as quick segmentation between surface and terrain. For archaeological use it is mainly the last pulse that is of interest, since this depicts the terrain and contours of archaeological structures in the terrain (Hyyppä et al. 2009, 336), resulting in the reduction of point density used for analysis. Further, data for archaeological LIDAR is often delivered as points in gridded space structured as one point per square meter to represent a mean value of original density to reduce file size. Calculating points to a grid by computing cell elevation values by a mean through a neighborhood defined search radius, can also help standardize data, but as a result also smooths data out to visually omit details in the landscape. However, many deliverables of public DEMs are already gridded into regularly gridded cell interpolations representing specified distance values, i.e. DEM1 or DTM1 as 1 meter grid, and DEM10 or DTM10 as 10 meter gridded cell values to represent point densities exceeding defined resolution. As a result, maximum resolution scale is defined by a singular point of unknown local point densities, meaning level of detail in the landscape cannot be verified. Nonetheless, if local point densities are sufficient for digital landscape representation, it is an efficient way of handling point clouds by user friendliness through improved computation by file size.

2.4 THE LIDAR PRODUCT

The LIDAR product is point clouds in 3dimensional space based on the recording of tangible 3dimensinal information. Airborne LIDAR can offer similar landscape information as aerial archaeology, but adds a dimension based on elevation data. Aerial archaeology offers a passive remote sensing technique recording the reflected part of the visible and near infrared spectrum. The LIDAR product, on the other hand, offers an active technique by measuring dense clouds of surface information capable of dynamic segmentation based on classification of points. A laser pulse can penetrate vegetation to a certain degree, making it possible to distinguish and discriminate different objects within the footprint (Doneus & Briese 2006, 99-100). The LIDAR product offers possibilities of interpolation and modelling of landscape and objects in accordance to defined criteria in order to visualize specific requirements. Thus, if proper processed and manipulated, data can be filtered to reveal different manipulated landscapes, such as only points of terrain by removing vegetation, construction, and all other features above bare-earth. This ability provides a new layer for understanding the landscape surrounding us, often revealing details that were long forgotten. LIDAR sensors are mounted on different platforms, mobile or static, terrestrial or airborne. LIDAR data is especially useful for mobile platforms due to the capabilities of continuous large-scale measurement of points. The common mobile platforms are satellites, airplanes, unmanned aerial vehicles, and vehicles. The principle of LIDAR is the emission of light towards any given surface, which is then reflected and echoed back to the sensors. The LIDAR scanner emits rapid pulses of light at any given surface, and amount of return signals is defined by the LIDAR instruments capability to record and store the return of the pulsed light photon. The amount of returned light is determined by internal and external factors. Internal factors are software and hardware, whereas external factors are atmospheric and surface conditions. A basic raw LIDAR point consists of XYZ position often coordinated to a Global Positioning System, GPS, together with orientation by the local Inertia Measurement Unit, IMU, measuring angle and range. These parameters construct a point in Euclidian space of any given surface. The result is the base of any spatial measurement transformed to a Cartesian plane with the Global Positioning System. The Euclidian space is the geometrical axiom in space, but usually transformed to reference a certain method of representation in a Cartesian plane, e.g. a coordinate system. Presently there are two standards of LIDAR scanning by the documentation of light. The first consist of conventional scanners that record discrete echo return signal, i.e. measurement of signal peak by separation. The second consist of Full Waveform scanning, FW, recording the whole return as one continuous wave. FW LIDAR can also be segmented and counted by peaks to make it discrete (Lasaponara et al. 2011, 2062). FW LIDAR further allows extended segmentation by improving the wavelength extension to classify signal returns terrain and off terrain objects, such as vegetation, natural objects, and man-made objects in connection to the terrain (Doneus et al. 2008). This makes it possible to distinguish between return signals by canopy penetration, producing more accurate Digital Elevation Models.

The outcome of LIDAR scanning is typically Digital Elevation Models (DEMs) derived from recorded 3D point clouds. Two major outcomes of DEMs, are: Digital Terrain Models (DTM) of the bare earth, and Digital Surface Models (DSM) with canopy details (see also Figure 2). For detection and management of information from the past, especially the DTM reveals important information for understanding, investigating, and managing sites and landscapes of cultural heritage interest. In order to perform comprehensive investigations of spatial context and cultural and temporal impact on landscape, it is necessary to understand and analyze procedures and methods to retrieve correct ground truth of comparable data and site information. Consequently, techniques and methods need as much attention as results. Scanning results are already manipulated data, and as such often strongly related to specific research questions. Hence, data retrieval and manipulation need proper assessment and analysis before any conclusions can be finale. Utilization of LIDAR data could easily become the standard from which cultural heritage monument detection and management could be initiated for a cost-effective approach for large-scale handling and processing. However, it is necessary to remember that LIDAR only documents the physical presence of the surface and terrain, and thus only cultural heritage monuments in the landscape with physical manifestation. Further, as landscape is segmented into surface and terrain models, it is necessary to note the filtration process used to remove modern construction and vegetation. Because, the algorithmic procedures for segmentation between surface and terrain do not discriminate between human made structures of the past and the present. The DTMs therefore only represents monuments of the past that has become part of the terrain by elevation differences inside the parameters set for segmentation of landscape. Segmentation of the landscape for definition of surface and terrain models can be filtered by many different algorithmic approaches, which all indicate slight differences in how to understand the landscape (Silthole 2005, 13-28). The parameters for the algorithmic filtering are based on available data structure of the individual LIDAR points. The individual LIDAR points typically also contains information for segmentation based on intensity reflectance value due to multiple point measurements, recording first and last pulse values, making it possible to discriminate data based on more information than elevation and geometrical shape of structures and landscape. Segmentation based on filters of elevation and geometry revolves around four concepts:

1. Slope based – Algorithms where slope is determined by difference of height between two points. Highest point within a certain threshold is assumed to belong to a group or object.
2. Block-minimum – Horizontal plane with corresponding buffer zone above. The horizontal plane locates buffer zone, and the buffer defines zone where bare earth points are expected to reside
3. Surface based – A parametric surface with a corresponding buffer zone above and below. Similar to before, the buffer defines zone where bare earth points are expected to reside.
4. Segmentation by clustering – Segmentation by cluster algorithms defines entities based on clustering according to defined modularity. Any points are defined to belong to the cluster if the cluster value is above the neighborhood. The neighborhood expands into higher level structures allowing classification based on spatial organization of surface in a point cloud.

Silthole 2005, 30

Digital objects or entities in LIDAR data can also be filtered based on rules of continuity of discontinuity. A building, for example, breaks the continuity of the terrain. Some of the measures of continuity and discontinuity are based on: height differences, slope, and shortest distance to defined surfaces. However, everything is dependent on means of measurement, data structure, and information contained in the individual point. Many studies have shown that using the full waveform of LIDAR data can aid in understanding and extracting information from the landscape (e.g. Anderson et al. 2006; Briese et al. 2013; Briese et al. 2014; Doneus & Briese 2006; Höfle et al. 2012; Lasaponara et al. 2011). Many more algorithmic procedures exist for filtering data into segments or classification, and it is a process that keeps evolving to incorporate more and more variables to produce better data. The general circumstances making filtering methods difficult can be described as: 1. random errors, 2. geometric complexity, 3. geometric discontinuity, 4. geometric fusion, 5. low vegetation, and 6. dense vegetation. These six circumstances have large impact on the potential for segmenting and classifying any landscape, which especially for the classification process results in the detection of false positives while omitting others. Thus, even in trying to reconstruct landscapes by surface or terrain values, it needs to be questioned to which degree a digital landscape is a true depiction of natural and cultural tangible values. Because, all remotely sensed data is a designed representation of real-world entities, manipulated to make sense to any given target. As a result, the desired terrain segmentation for an archaeologist might be different than that of geologist. The archaeological main concern would be that of the cultural terrain, whereas the geological focus would be on the natural terrain. Thereby not defining that one is not important to understand the other, but a burial mound would be extremely urgent to keep in the digital representation from an archaeological point of view, and would be much less important from a geological perspective.

FIGURE 2: A SIMPLISTIC REPRESENTATION OF DIFFERENCE BETWEEN DSM AND DTM. SURFACE MODELS INCLUDE STRUCTURES AND CANOPIES

2.5 UNDERSTANDING LIDAR

The LIDAR equation is similar to RADAR, and relates to the power of emitted light and return signal. LIDAR datasets provides series of point based energy recordings reflecting any given surface. In this study, particular interest is on its abilities for terrain registration and canopy documentation. LIDAR measurements are recorded by static scanners or scanners mounted on moving airborne or terrestrial vehicles to cover large areas. The power of LIDAR data is especially recognized by its ability to cover large areas, but static Terrestrial Laser Scanning on fixed positions is also of growing importance for complex site investigations (Doneus et al. 2010; Cheng et al. 2016). LIDAR is a multi-sensor measurement system capable of incorporating multiple sources following time-synchronized components. The components consist of a global positioning system (GPS) determining absolute position by 3dimensional XYZ space. From this fixed position everything is synchronized by angle, distance and reflection. The laser range finder operates by this two-way travel time of a pulse of laser light, often in the near infrared electromagnetic spectrum (Figure 3). Distance in this two-way travel from scanner to terrain or canopy is calculated by:

EQUATION 1: TRAVEL TIME CALCULATION

$$r \; [\, r = c \cdot \Delta t/2 \,]$$

Δt is travel time, and *c* is the known speed of light (Geist et al. 2009, 312).

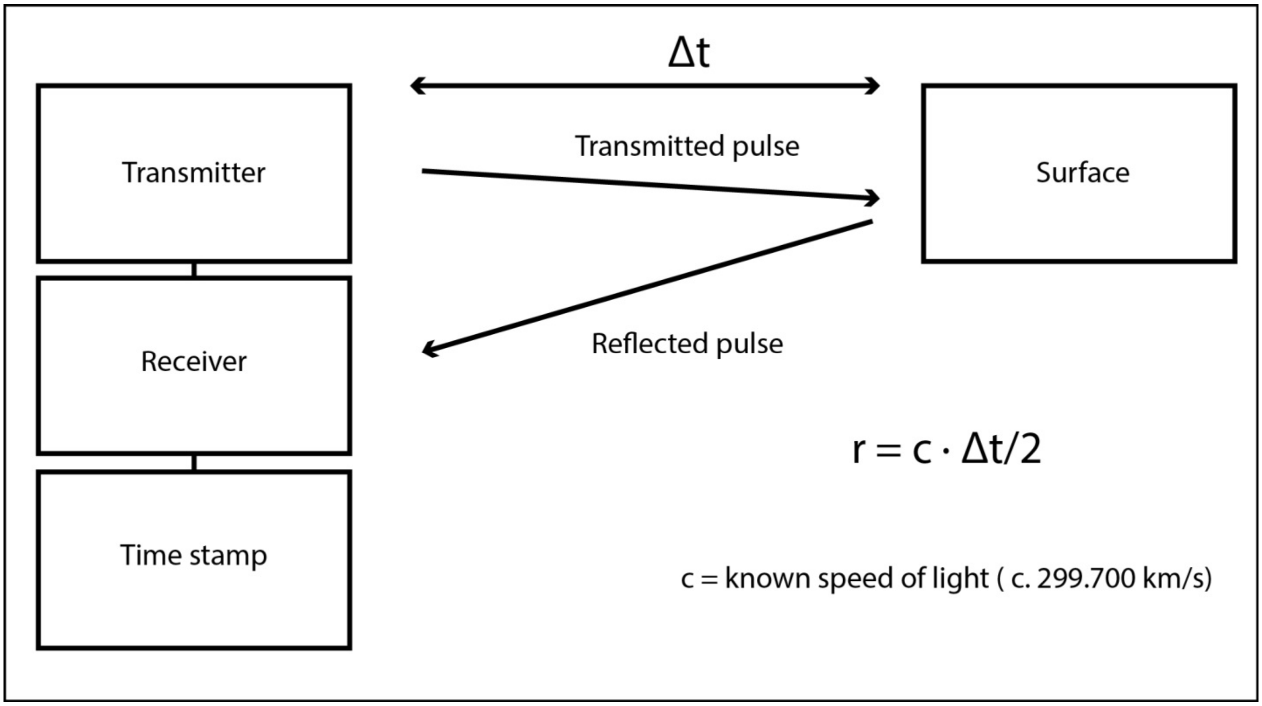

FIGURE 3: THE PRINCIPLE OF LIDAR RECORDING

The means of calculating travel time can be different based on system parameters, which in return also have an effect of the area scanned. The two standard means of distance calculation are Time-of-Flight (TOF) and Phase-shift (PS) (Alonso et al. 2011). The two technological approaches are applied to different spheres due to the capabilities of accuracy and acquisition rate. TOF enables long range scanning, while PS typically is applied to short distance scanning for more accurate data with high acquisition rates. The two approaches have been developing towards each other with PS extending range, while TOF have been increasing the acquisition rate. TOF scanners calculate the individual short pulse emitted from the scanner, and the time it takes for the pulse to return after reflection on a given surface. PS scanners calculate a continuous beam of emitted laser, and calculate the phase shift between the emitted and received laser beams. This also makes the difference in potential of full waveform recording, because PS scanners return data stream rather than discrete time-stamped points, which in return makes it more optimal for intricate and detailed surface information, such as dense forest canopy. Because, the two different measurements produce different results dependent on scenery circumstances. As a consequence, a scanner is not just a scanner. A scanner is produced towards a specified task. Range, conditions, and scenery circumstances determine which techniques are more applicable.

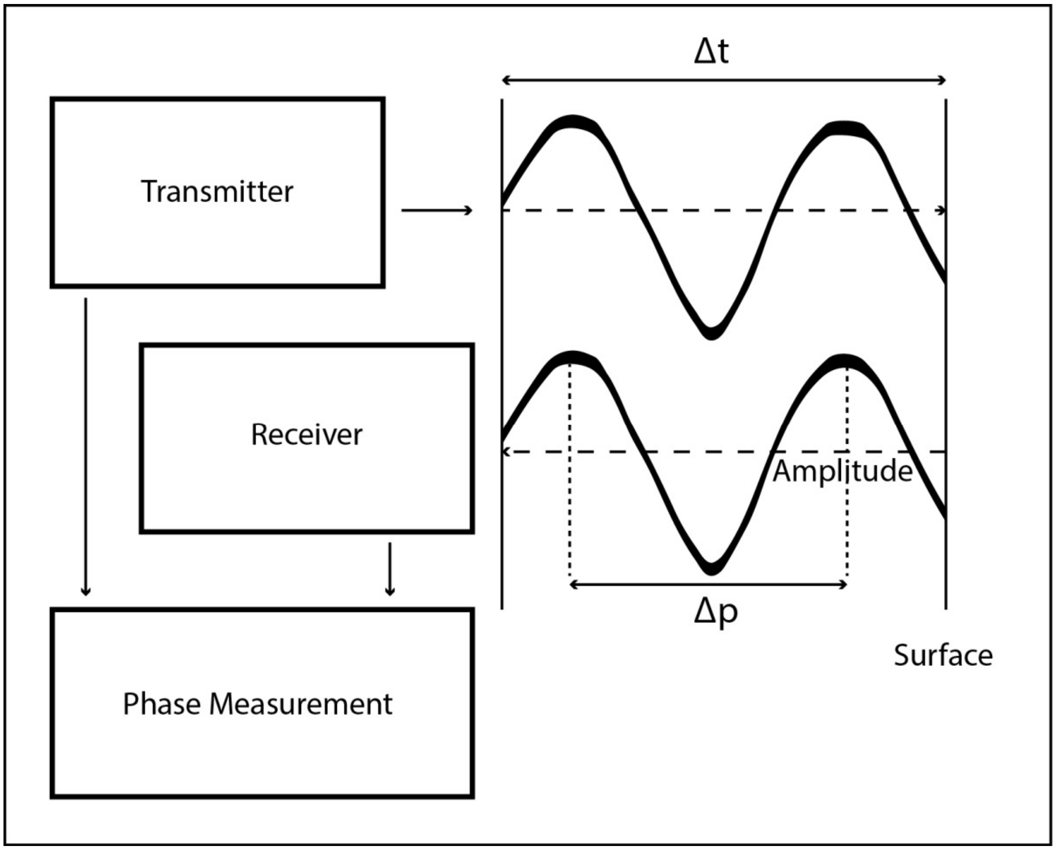

FIGURE 4: PHASE-SHIFT (PS) MEASUREMENT BETWEEN TRANSMITTED AMPLITUDE AND REFLECTED AMPLITUDE TO CALCULATE DISTANCE

The phase measurement for PS is the difference between transmitted amplitude and reflected amplitude of the pulse, *Δp (*Figure 4*)*. The transmitted amplitude is measured in order to determine the distance of the travelled pulse. The distance between the receiving wave amplitude is then measured and compared to the distance in the transmitted amplitude. The accuracy is determined by the length of the cycle of periodicity and wavelength ambiguity in the range of estimation (Alonso et al. 2011, 378). The principle are similar to TOF by distance calculation (Amann et al. 2001, 12), but the necessary length measurements provides some fundamental difference. This results in different scanners using different means of distance calculation, based on necessity of reproducing at different scales with phase-shift calculation used for larger point-clouds, and time-of-flight for smaller point cloud production (Alonso et al. 2011, 385).

2.6 ACTIVE SENSING VERSUS PASSIVE SENSING

No matter the distance calculation, LIDAR data is active sensing by producing its own energy for recording the area of interest through the emission of light. Passive sensing records environment levels based on existing light and energy sources. The majority of remote sensing is done by passive sensing where the sun is the main component of ambient energy source. This is evident by the large field of aerial archaeology and spatial understanding by aerial and satellite imagery. The field of passive sensing within archaeology is also focused on the irregularities between natural and cultural distributions of patterns of static energy recordings. This is for instance present in the use of aerial thermal infrared recordings increasing the wavelength at which images can be produced to potentially reveal buried structures. Normal passive aerial photography can equally reveal buried structures, but the increase in thermal multispectral imagery has increased the potential by increasing the wavelength range at which images can be acquired (Bewley et al. 2011). Equally, hidden sub-soil features change the circumstances for which external factors interact with the top- and subsoil producing inhomogeneous distribution of humidity. This, in result, affects soil density, color, and physical state of vegetation (Scollar et al. 1990), as well as the thermal and electric capacity and conductivity (Orlando & Villa 2011, 155). Thermal sensing includes passive sensors to register energy emissions in the landscape, such as natural energy emissions and latent sun capture in landscape and canopies. The future of remote sensing therefore perhaps lie in a combination of active and passive sensing in order to improve archaeological feature detection by adding more bands of wavelength recording by multispectral LIDAR.

Because, points of data are not confined to only depict spatial value within the data structure. By recording multiple wavelengths and by attaching and calibrating a camera to the scanner (Figure 5), spectral bands can be derived from raw radiometric measurements as physical quantification of absolute values reflecting external factors. Thus it combines active and passive sensing. Multispectral ALS especially derives value for understanding acquisition parameters and atmospheric conditions, such that backscattering can be normalized for comparison and standardization between different study areas (Alexander et al. 2010). For TLS, radiometric calibration is equally necessary for potential comparison between scanned data. For the TLS, the radiometric value is not as important for determination of external parameters of scanning, such as atmospheric conditions, because weather condition is not as dynamically changing and affecting local environment for scanning. TLS is easier to strategically complete when conditions are locally deemed sufficient, and the amount of return signal is not as important due to large quantities of emitted pulses and scale of area investigated. This makes radiometric calibration less important for

TLS, but very important for ALS towards standardizing datasets. Multispectral LIDAR can also provide information in wavelengths outside of the human visible range, making it possible to record additional variables for segmentation and classification.

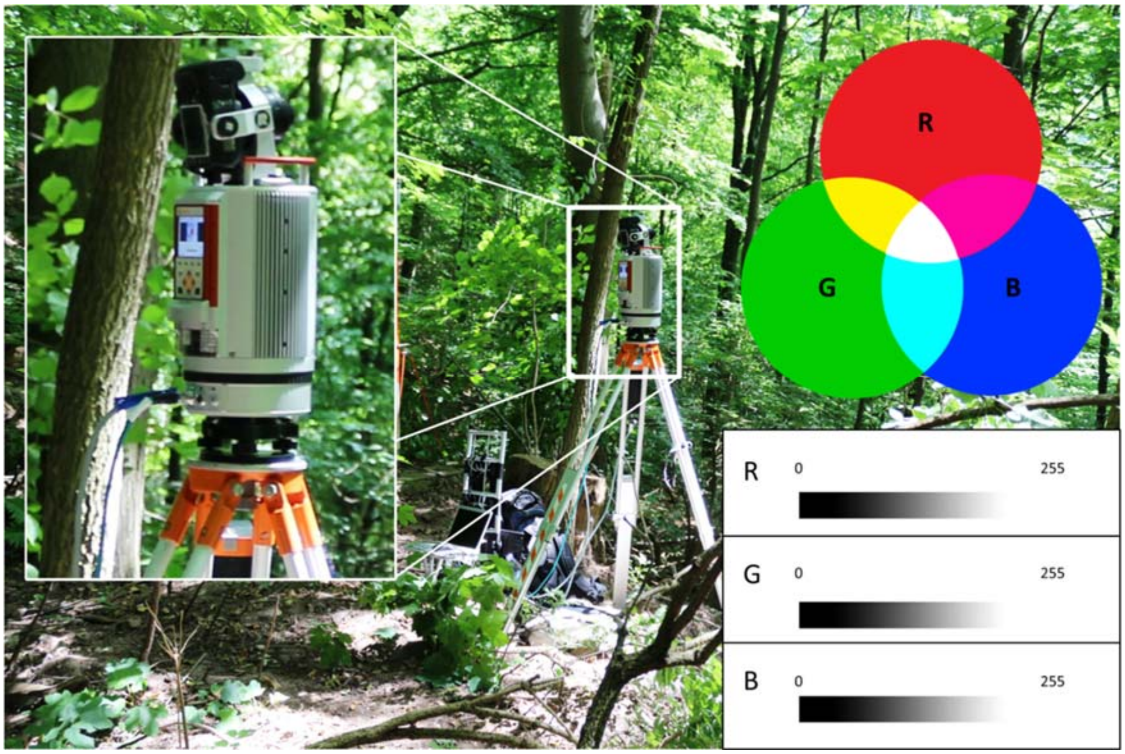

FIGURE 5: A RIEGL VZ-400 ON SITE IN DENSE VEGETATION. ATTACHED IS HIGH-RESOLUTION CALIBRATED FISH-EYE CAMERA FOR CAPTURING RGB COLORS

The human perception is multispectral sensing, meaning it can sense beyond one spectrum. Human perception especially responds to the red, green and blue wavelength regions forming an adapted hue color spectrum from *RGB* to identify the world. However, the human range of perception of the electromagnetic spectrum lies in a very small region of the visible range. The visible range corresponds to wavelengths in the range of 400 to 700 nm, or 0.4 to 0.7 µm, with a color range of violet through red. The visible colors are constructed from shortest to longest wavelength from: violet, blue, green, yellow, orange, and red. Ultraviolet wavelength is outside of the humanly visible spectrum, but can be recorded and manipulated to be shown within a human visible range. Ultraviolet radiation has a shorter wavelength than the visible violet light, whereas infrared radiation has a longer wavelength than visible red light. Meanwhile, sunlight consists of the entire electromagnetic spectrum, and is reflected and absorbed within and beyond the human range of perception. White is the mixture of colors in the visible spectrum, and black is the total absence of light in any spectrum. This gives the gradation of the natural amplitude of the visible spectrum from

1 to 0, of presence or absence. The image gradient for RGB is typically structured by 0 to 255 as the scale from no presence to presence, and can be computed as gradient scales for edge and texture matching to detect features or densities. For a long time within remote sensing, it was the hope that computer assisted interpretation would lead to the identification of unique spectral values to classify the world. For archaeology it is still one of the primary areas for non-invasive archaeology and detection of sub-soil evidence. However, no unique identifiers work for all contexts, meaning environment has a large influence on the possibilities of non-invasive sub-soil feature detection. Different wavelengths are as a consequence more applicable in certain contexts compared to others, because passive sensing records natural absorbed and emitted energy by the surface and terrain. For active sensing, such as multispectral scanning with controlled exposure to certain wavelengths, it is also quite clear that certain wavelengths are more applicable than others. For instance, vegetation has a wide array of wavelengths usable depending on vegetation type and potential moisture, e.g. broadleaf versus needle (Eastman 2001, 21). Multispectral wavelengths are also used for the 'landuse' classification from the NASA and USGS LANDSAT 1 to 8 series, and continue to be of use for a wide array of scanning and recording for understanding landscape. The basic spectral bands for Earth monitoring is constructed to use the red, near infrared, and green bands to construct pseudo colors for information extraction from the landscape. This has formed the classical indices for vegetation classification based on the *normalized difference vegetation index,* NDVI, which follows:

EQUATION 2: NORMALISED DIFFERENCE VEGETATION INDEX.

$$NDVI = (NIR - R) / (NIR + R)$$

NIR = NEAR INFRARED, R = RED

NDVI is a calculation that has proven to be efficient in distinguishing between vegetation and other structures interaction with the electromagnetic spectrum (Eastman 2001, 32). Using near infrared for the detection of vegetation indices to determine potential archaeological features is an added dimension in aerial archaeology (Bennett et al. 2012; Lasaponara et al. 2008). The NDVI reveals vegetation indices by photon absorption from spectral composition such as plant growth based on levels of low or high natural stress variables in certain contexts, i.e. plant growth on buried archaeological features (Figure 6).

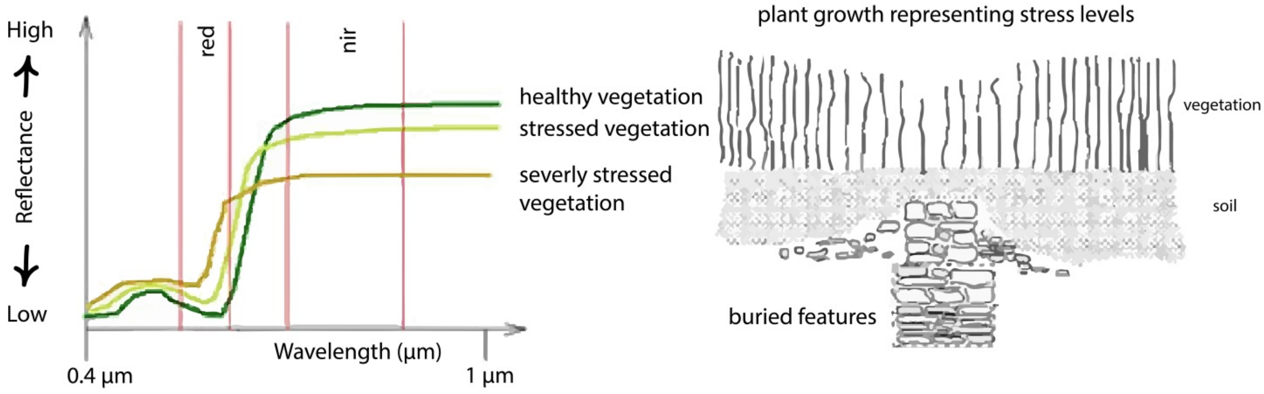

FIGURE 6: RECORDED POTENTIAL WAVELENGTH COMPOSITION FROM HEALTHY OR STRESSED PLANTS IN DRY CONTEXT (LASAPONARA & MASINI 2012, 26)

TABLE 1: LANDSAT 5 AND 8 BAND AND WAVELENGTH COMPARISON (USGS LANDSAT)

Landsat 5 Thematic Mapper (TM)	**Bands**	**Wavelength (µm/micrometers)**	**Resolution (meters)**
	Band 1 - Blue	0.45-0.52	30
	Band 2 - Green	0.52-0.60	30
	Band 3 - Red	0.63-0.69	30
	Band 4 - Near Infrared (NIR)	0.76-0.90	30
	Band 5 - Shortwave Infrared (SWIR) 1	1.55-1.75	30
	Band 6 - Thermal	10.40-12.50	120* (30)
	Band 7 - Shortwave Infrared (SWIR) 2	2.08-2.35	30
Landsat 8 Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS)	Band 1 - Ultra Blue (coastal/aerosol)	0.43 - 0.45	30
	Band 2 - Blue	0.45 - 0.51	30
	Band 3 - Green	0.53 - 0.59	30
	Band 4 - Red	0.64 - 0.67	30
	Band 5 - Near Infrared (NIR)	0.85 - 0.88	30
	Band 6 - Shortwave Infrared (SWIR) 1	1.57 - 1.65	30
	Band 7 - Shortwave Infrared (SWIR) 2	2.11 - 2.29	30
	Band 8 - Panchromatic	0.50 - 0.68	15
	Band 9 - Cirrus	1.36 - 1.38	30
	Band 10 - Thermal Infrared (TIRS) 1	10.60 - 11.19	100 * (30)
	Band 11 - Thermal Infrared (TIRS) 2	11.50 - 12.51	100 * (30)

Similarly, LANDSAT 1 to 5, recorded between 1972-2013, was focused on pseudo color generation and the creation of vegetation indices for classification, but LANDSAT 5 included a thematic mapper to include mid-range infrared with seven bands added to the data structure. The amount of bands for wavelength documentation is, however, only confined by hardware and range of applications envisioned. For instance, the LANDSAT 5 Thematic Mapper recorded seven spectral bands in different wavelengths, whereas the LANDSAT 8, from 2013 to present, expands the band range with eleven bands to include a wider range of wavelengths (Table 1).

Equally, promising steps are undertaken to map the potential use of multispectral LIDAR (Briese et al. 2013b; Wichmann et al. 2015). By the study of Wichmann et al. (2015, 118), it is shown that combining active sensing and passive sensing can improve classification accuracies. Briese et al. (2013b, 123) show the practical potential of calibrated radiometric information for LIDAR data for archaeological prospection and future ideas for usage of multi-wavelength LIDAR data for different applications. Thus, the range of potential application by adding different wavelengths to remotely sensed data and LIDAR data is still a field expanding with a great potential of adding multiple variables to the detection of archaeological details above and below ground.

2.7 GEOMETRIC AND RADIOMETRIC CALIBRATION

Calibration of LIDAR data is essential for a wide range of applications and means of standardization. Calibration by geometric and radiometric calibration aims at standardizing data and removing systematic errors from the point clouds. Random errors occur despite calibration, but can be removed by other means. Geometric and radiometric calibration is especially necessary for the comparison of different scanning sessions, such as in between archaeological site comparison or flight strip correlation. Systematic errors are related to setup and environment, and the errors can be unique based on the parameters influenced in the specific scanning session. The systematic errors mainly occurs by bias in system parameters, such as mounting parameters and changing system components of range and angles (Habib et al. 2011). This is rectified by standardized calibration and data-driven strip adjustment to compensate for systematic errors (Friess 2006; Skaloud & Lichti 2006; Glira et al. 2015). The construction of systematic errors by scanning is created by imperfect instruments, incorrect registration, or deficiencies in the mathematical models used (Friess 2006, 2). Systematic errors can be compensated, because they follow rules and patterns based on variables of equipment and circumstances, whereas random errors occur based on internal and external irregularities. The imperfect instruments can be corrected or updated, registration of data can be re-positioned, and mathematical models rerun. Random errors are more difficult to deal with in the pre- and processing stages of data collection and registration, but possible to correct in post-processing stages of data management. Systematic errors can lead to erroneous data collection, and is therefore more necessary to address in the pre-processing stages, but can as well be addressed in the processing stages of data construction. Random errors cannot be accounted for, before a degree of analysis is carried out. Random errors occur due to light reflection problems, moving objects, and human errors. For the reflection of emitted pulse, the reflection can be affected by wet surfaces and water in general. Reflection of light within wet surfaces and water can be dispersed because of a lack of clear surface, resulting in light sometimes bouncing back to the receiver, but often not. Similar to the reaction of light illuminating a crystal, light disperses into many directions when in contact with water making the amount and intensity occur randomly. Random errors also occur by moving objects which based on the resolution of the scan can be different. TLS is affected by many small changes in the scenery, e.g. canopies changing position because of wind, living objects moving into scanning range, and environment. ALS is less affected by details due to the resolution of the scan, but still detects similar instances of irregularities needed to be filtered. Especially weather conditions affect ALS. In both instances of TLS and ALS, many irregularities is compensated by increased amount of scanning positions and angles from which terrain, objects, and canopies are scanned. Increased amount of positions can counter moving objects by defining them as random errors and outliers not part of the static scenery intended for scanning. The algorithmic approaches is defined by experience, but especially for automation, procedures become estimations based on simulated case studies for correction of systematic and random errors during scanning. Simulated estimation of standard deviations based on systematic and random errors help minimize misleading data by determining potential impact on data and means of correction. The theoretical accuracy is determined by the computed error of covariance propagation, giving standard deviations as valid measure of laser point accuracy. The importance and significance is evident, because the system parameters compute based on observation of angle, range, position, and orientation. An offset of $\Delta\Theta=0.008°$ can therefore lead to a constant error capable of skewing true accuracy and position (Figure 7), evident by the simulated scans of Peter Friess to merge airborne LIDAR data (2006).

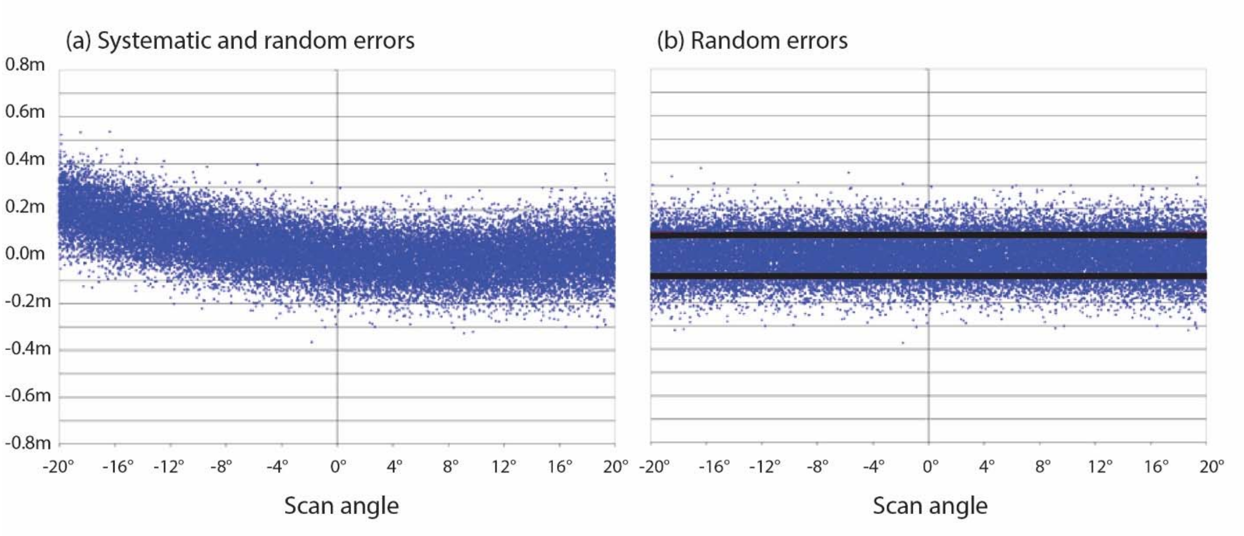

FIGURE 7: A AND B SHOW TRUE ERRORS OF HEIGHT FROM THE SIMULATED STUDY. B SHOWS STANDARD DEVIATION BY INDICATED LINE. THE POINT CLOUDS WERE CONFIGURED WITH ERRORS. A SHOWS INCORRECT INSTRUMENT PARAMETERS, BY: SCAN-ANGLE [OFFSET ΔΘ=0.008°], SCANNER SCALE ERROR [ΔS=0.001], WITH A FLYING HEIGHT OF 1000M (AFTER FRIESS 2006, 2).

The random errors are constant and produce similar outliers, whereas the systematic errors can skew accuracy and position leading to incapable comparison between different scanning positions, strips and/or sessions. Thus, for standardizing data, it is necessary to also understand the processing of the point cloud by random errors as well as systematic errors in order to fully comprehend correlation of data (Burman 2000; Glira et al. 2015; Ressl et al. 2008). Friess 2006 uses the redundancy in the overlapping areas of flight lines to estimate correction for observations of instrument parameters to produce more complete and correct point clouds. This is done to understand point cloud adjustment, but also to automate point cloud processing (Friess 2006, 7). From processing the point cloud to correct for errors, standardizing data structure, and add variables, it is possible to work directly on the point cloud to analyze and interpret data. However, simply to navigate in the point can be computational heavy, as well as humanly intangible to comprehend. As a consequence, LIDAR is transformed to more simplistic format by interpolating data to vector- or raster-based DEMs (Hengl & Evans 2009).

2.8 BATHYMETRIC LIDAR

On a side note, it also has to be mentioned that both airborne and terrestrial LIDAR can be used for underwater scanning. Bathymetric LIDAR will not be the focus of this investigation, but it has to be mentioned how bathymetric LIDAR functions. Underwater scanning is essential for many fields for understanding underwater morphology, biology, and human impact. Within archaeology it is primarily focused on understanding sunken artefacts and landscapes of the past. Presently bathymetric LIDAR has some limits in regards to scale of precise scanning range, making it more suitable for shallow water investigations, such as intertidal and near shore zones. These areas are also the most relevant areas for understanding human dispersal and use, since the near shore areas consist of the most significant areas for past exploration of resources and settlement (Doneus et al. 2013a, 2136). Deep waters have naturally also played a significant role for past human activity, such as for deep water fishing and transportation of goods. The remains of previous activity on deep water, is, however, affected by the current and open bed floors, resulting in the dispersal range encompassing waste areas. In shallow waters, the potential of conservation is greatly improved because of gyttja and the encapsulation of materials in anaerobic layers of sediments, and the potential of less dispersal of materials. The effectiveness of bathymetric LIDAR is reflected based on the composition of substances in the water. The composition of substances in water, such as in gyttja rich areas, complicates the potential of bathymetric LIDAR by presence of dissolved organic matter, phytoplankton, and minerals. This is due to problems of reflection and absorption of light photons in turbid waters with high organic levels. In the element of water, the penetration and reflection of light is not as controlled due to light dispersal and absorption of light photons, also meaning return signal will have different intensity levels. Substance composition in different waters requires different means of adaptation in relation to photon absorption and scattering due to minerals, yellow substance, and phytoplankton (Silva et al. 2008). This is especially problematic in the near infrared of laser light, but can be compensated to some degree by the use of emitted pulses in the green specter of light. The green spectrum of light with longer wavelengths has proven to be the most efficient spectral region for water penetration (Doneus et al. 2013, 2138). As with all kinds of Laser Scanning, it is important to understand environmental variables in order to construct digital documentation of landscape. Bathymetric LIDAR, however, helps push the boundaries and possibilities of LIDAR data by operating in very difficult scanning circumstances. For now, however, it is necessary to differentiate between the spectral bands above and below water.

2.9 LIDAR INTERPOLATION

The interpolated raster data, commonly used within archaeological practice, are the transformation of data from points to gridded data. A raster is constructed of pixels arranged in order by an outlined grid of specified dimensions. Each pixel contains given information in a range between minimum to maximum outlined by spectral band definition. Compared to large datasets of vector data, raster image is a more efficient way to display consistent large areas of information. The reason for this is human logical reading of gradients versus absolutes. Vector can also be graduated, but will always consist of gaps. Interpolated data constructs value in between points of information, e.g. by the nearest neighbor algorithm, thus filling gaps. The gradient value of interpolated data is determined by choice and source. Usually the standard of LIDAR data is an 8-bit integer value between 0 to 255, e.g. from black to white as indication of relative elevational scale (Fischer et al. 1996, 239), thus a 3dimensional visualization on a 2.5dimensional plane. By 2.5dimensional plane, the definition is that it is not true a true 3dimension, because interpolated data is the construction of a grid draped upon data. Thus, a LIDAR point is in itself 3dimensional, but the LIDAR interpolation is a visualization fixed to a 2dimensional plane. Controlling the transformation of data by interpolation, is therefore of absolute necessity. This is especially true since LIDAR has become an important and integral part of an objective approach to visualize and understand the landscape on both micro- and macro-scale. Archaeological LIDAR is simplistically often defined as an interpolated raster derived from LS, and often visualized by the hillshade algorithm from an artificial setting sun in the west. This standardized visualization of landscape for archaeological studies makes data comparable because of similar expression. None the less, it also results in data not revealing everything hidden within the DEMs. But, any interpolated visualization is biased towards certain details in the landscape, and potentially visually omitting others. DEMs are interpolated as digital representations of relief over space. DEMs are either vector- or raster-based to be used in three different data structures (see also Figure 8; Masini et al. 2011, 268):

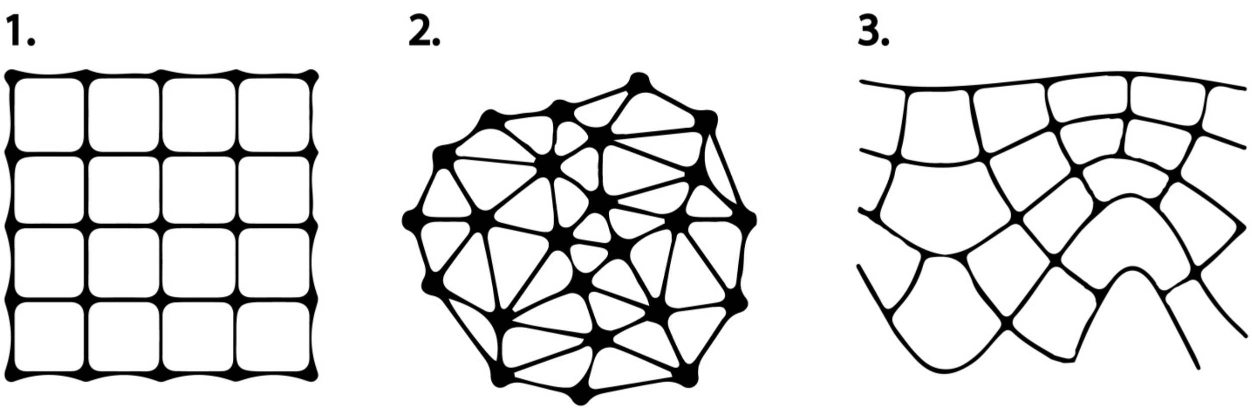

FIGURE 8: STANDARD INTERPOLATED DEM DATA STRUCTURE: 1. GRID OF A REGULAR SQUARE MATRIX DRAPED ON A DEFINED PLANE WHERE EACH PIXEL REPRESENTS ELEVATION, 2. TRIANGULATED IRREGULAR NETWORK, TIN, MESH TO MODEL SURFACE AS CONTIGUOUS NON-OVERLAPPING TRIANGLES, 3. IRREGULAR POLYGONS TO MESH SURFACE BASED ON CONTOUR LINES AND ORTHOGONALS (AFTER MOORE ET AL. 1991, 4)

Regular gridded DEMs are the standard means of algorithmic interpolation of data, but have the disadvantage of not being able to properly represent abrupt discontinuity in the landscape, and smooths out details in very flat areas where data is not present (Masini et al. 2011, 269). Gridded DEMs are raster-based, and even though some details might be lost in the interpolation, compared to vector-based interpolation, it also offers some advantages in the form of standardizing output for comparison. The grid heights of regular gridded DEMs are typically determined by approximation methods like inverse distance weighting, moving last squares, linear prediction, or kriging interpolation. These methods offer grid cell creation based on nearest neighbor principles, making data continuous. However, most are more relevant for datasets of large point distribution, i.e. site, structure or object distribution. Vector-based interpolation produces discontinuous interpolation, making it more possible to determine data gaps. The vector-based TIN interpolation produces a network of triangles between all point data, structured by maximum length and exponent of triangle edges. This makes TIN interpolation capable of representing missing data or data with extreme elevation difference to indicate roughness of landscape. As a result, areas with missing data or abrupt elevation difference will look unnatural compared to actual landscape if the point density is not high enough to smooth the abrupt change in the data. But even though the problem with TIN-DEMs can be the visualization of landscape as discontinuous, it is also its advantages such as highlighting data areas that are troublesome and incomplete for detection and interpretation. The last means of interpolation by irregular polygons also use vector-based representation, but follows linear interpretation based on input. Contour lines are determined, and gridded by irregular polygons between maximum and minimum. Contour lines smooth out data similar to a raster grid and shows landscape as very continuous. For archaeological LIDAR and archaeological mapping, the choice of interpolation is therefore not simply one over the other, but rather a qualified decision based on data resolution needed, and scale of investigation. This is especially necessary for constructing quantifiable and standardized LIDAR data, and sets the basis from which the landscape can be visualized. The landscape of investigation also determines the necessary data resolution needed from regularly gridded DEMs and inherent ppsm to be computed by. An example of amount of detail can be seen in Figure 9 below, by three interpolated continuous regular gridded DEMs by different grid size.

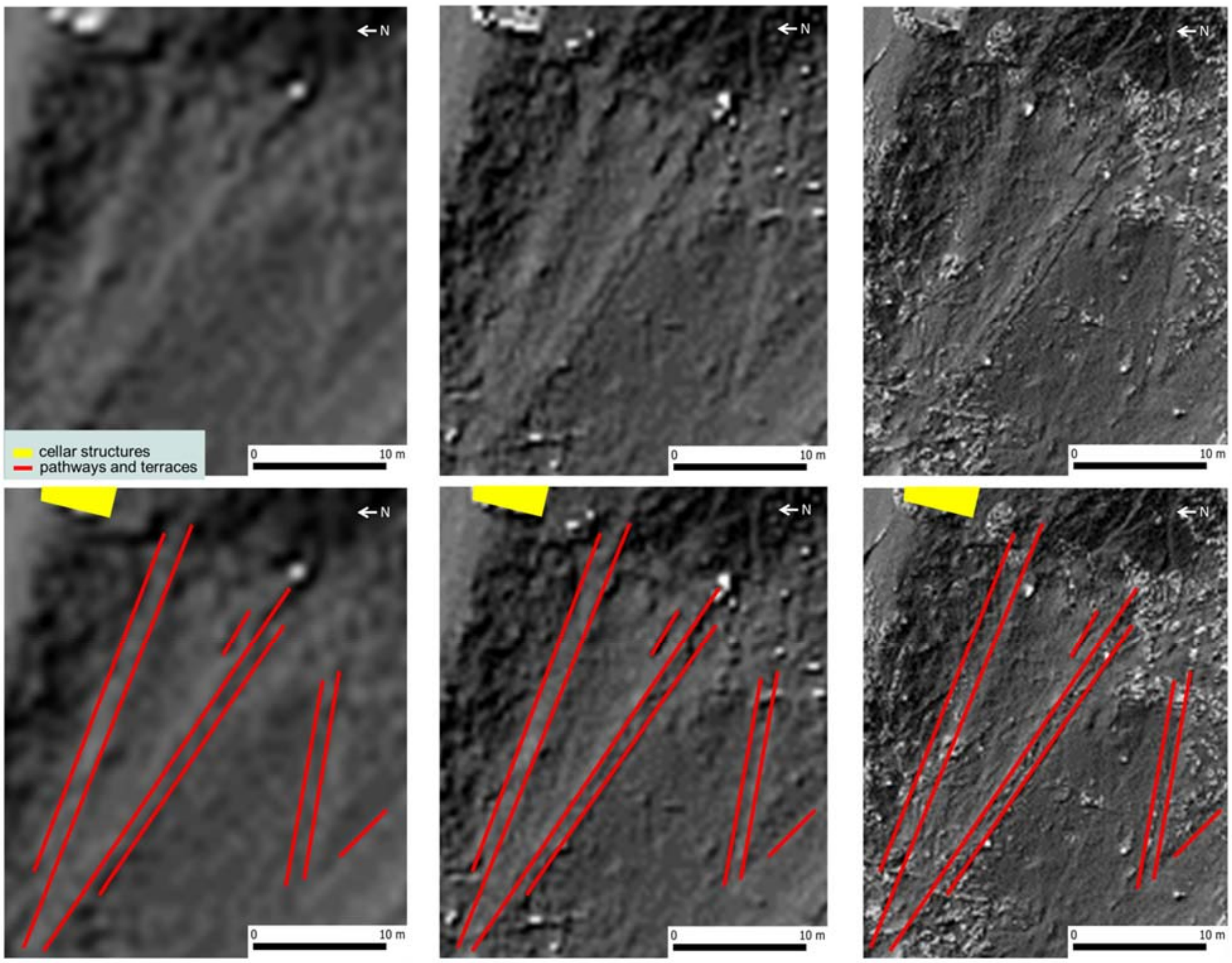

FIGURE 9: COMBINED TLS SCANS WITH DIFFERENT GRID SIZE. FROM LEFT TO RIGHT: 1 M, 0.5 M, 0.1 M. SHADED RELIEF: AZI. 45°, 270 ANGLE (RAUN ET AL. 2018)

To understand amount of detail needed for gridded interpolation, it is necessary to understand features in the landscape. The landscape in Figure 9 is from a dense forested landscape with both exposed and hidden archaeological features. For human and computational interpretation of the landscape, a lot of details in the landscape can be even more confusing for proper information extraction from the DEMs, meaning highest amount of detail is not always the best solution. Within the DEMs are pathways on a very sloped area, as well as cellar structures. The cellar structure is completely buried, and is only revealed as an unnatural elevation change in the landscape by ALS. However, since it is located right next to a modern road, it could easily be classified as something of no interest. The pathways in the landscape, however, reveal unequivocal evidence of past activity of interest for archaeological mapping from remote sensing. A closer view of the DEMs in Figure 9 reveals some of the changes in different grid size when interpolating. The amount of ppsm remains constant for the following interpolation comparison, and is retrieved by 12 different terrestrial scanning positions, of 14 scans in total with two additional scans in front of a cellar structure by point density changes between 8 to 3 mm at 10 m. The DTM was created by selecting minimum z-value per raster cell, resulting in some areas having vegetation as minimum z-value and consequently being included as terrain within the DTM. The 12 normal scanning positions were set at a resolution of 8 mm per point at 10 m distance. The additional two high resolution scans were of 3 mm per point at 10 m distance. In total 230.555.115 points were recorded for the 12 scanning positions with a resolution of 8 mm at 10 m, and the 2 additional scan positions included 24.469.696 points of 3 mm at 10 m. In total, the area scanned consist of c. 1.5 ha sloped hillside with dense vegetation, containing 255.024.811 points. The data processing procedures included data handling and manipulation for improved information extraction. The retrieved point clouds were processed in RISCAN PRO, operating and processing software for Riegl 3D laser scanners. The single scan positions were co-registered in RISCAN PRO by applying "Multi Station adjustment" with an average error of 1.17 cm. Individual ASCII text files were exported for each scan to be further processed in OPALS, *Orientation and Processing of Airborne Laser Scanning data* (Mandlburger et al. 2009). From OPALS, data was interpolated to DEMs of different grid size of 1 m, 0.5 m, and 0.1 m. Different means of visualizing the structured cells were attempted for interpolation, but a grayscale hillshade relief offers one of the best human readable ways of representing landscape for manual visual object detection of small and large structures. Especially the minor pathways were best seen by shading for indication of minor height differences, while still representing the generally sloped area.

The change in level of detail reveal that some details can be seen in the interpolated 1 m grid, but the amount of information is too low to distinguish them as being cultural traces left in the landscape. In the 0.5 m grid, the road and terrace structures can be distinguished as not being part of the natural landscape, and stands out as clear lines. In the 0.1 m grid, road and terrace structures are present and distinguishable as cultural traces left in the natural landscape. However, the amount of other details in the landscape also increases in the 0.1 m gridded interpolation. The visualization therefore becomes more blurred because more detail is revealed and information given. Thus, the high amount of detail in the interpolation with the highest amount of ppsm and information demonstrates not to be the most relevant or efficient for manual visual detection of objects and structures. The 0.5 m DTM reveals the same information in a simpler and faster procedure. The added amount of information is equally creating a more indistinguishable scenery for information extraction for both human as well as computational interpretation. This is evident in FIGURE 10 visualizing the 0.1 m gridded interpolation with linear features marked. From FIGURE 10, a large amount of linear features are distinguishable in the landscape, but 68 % of the linear features detected are of natural origin, i.e. fallen trees. 32 % consisted of culturally constructed linear features, i.e. pathways and terrace walls.

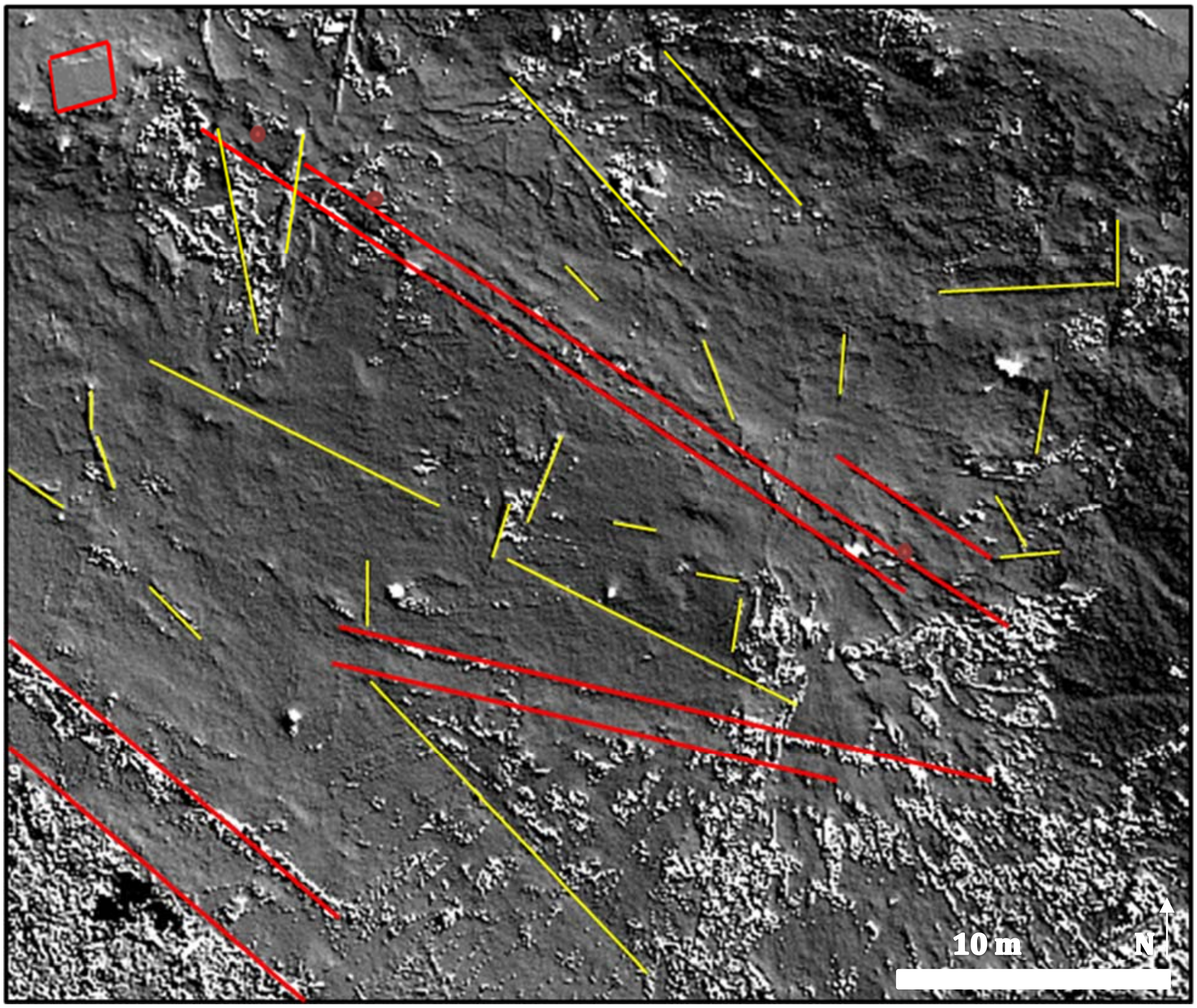

FIGURE 10: CULTURAL AND NATURAL LINEAR FEATURES WITHIN THE LANDSCAPE. NATURAL LINEAR FEATURES MAINLY CONSIST OF FALLEN TREES. SHADED RELIEF: AZI. 45°, 270 ANGLE.

RED: CULTURAL LINEAR FEATURES. YELLOW: NATURAL LINEAR FEATURES.

The results show that the highest amount of data is not necessarily the best approach. It is more relevant to focus on increased scanning positions and scale, instead of amount of detail recorded at each scanning position when documenting in dense vegetation. Because focused and structured procedures of scanning will in the long run produce the highest amount of information, and thus give the most complete picture of the area of investigation. ALS resolution consequently needs to include resolution capable of producing comprehensive 0.5 m gridded interpolations in order to become the effective means of large-scale cultural heritage detection. However, one approach cannot necessarily replace the other. Within the area of investigation, it is almost impossible to get a complete overview of the details and structures on-site. One of the major pathways within the area of investigation was not detected before a closer investigation of the TLS data was initiated. Since then the pathway has been confirmed as a ground truth, but the dense vegetation and collapsed trees made it almost impossible to detect by the initial fieldwork. It was only by knowing exact details from the TLS data, that it was possible to confirm this digitally detected plateau as part of the remaining cultural complex. Many other details were equally difficult to determine within the TLS data, and necessitated prior knowledge or later ground confirmation of its existence. Thus, all three data sources were necessary in order to construct a comprehensive overview of the cultural activities within the area of investigation, and none of them were completely capable of replacing the other. The study further investigated many different interpolated DTM's at different levels of detail. However, the most remarkably changes occur in the difference of grid size in the interpolation process. Increase and decrease in amount of information is not linear with amount of ppsm and potential amount of information and details in the landscape. Meaning, too much or too little information can be equally disturbing for archaeological information extraction. A 0.5 m DTM requires ideally 4 ppsm (see FIGURE 11), when not calculating for special circumstances, such as dense vegetation or extreme slopes.

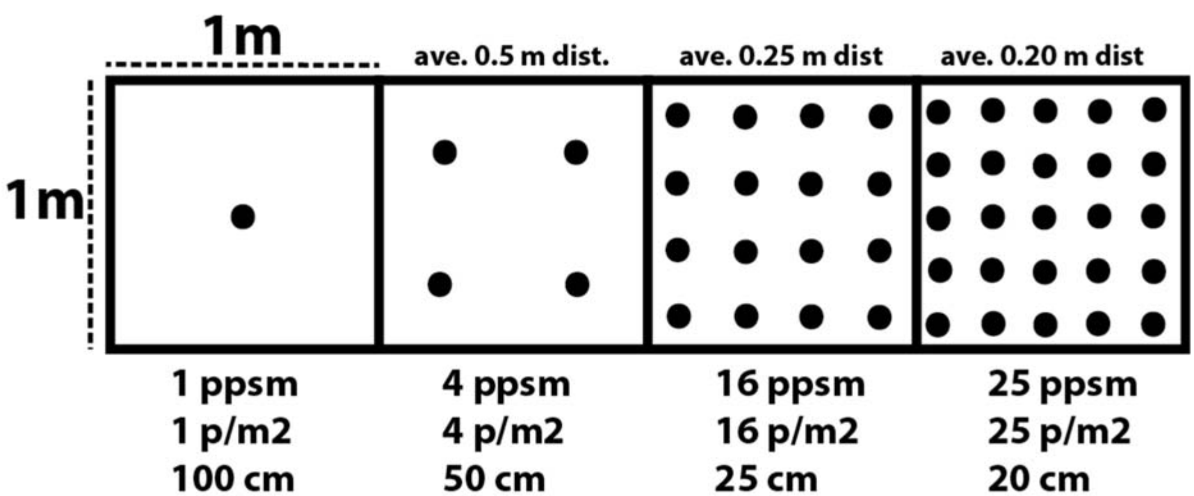

FIGURE 11: POINT DENSITY TO M^2

From LIDAR laser scanning in a simple flat landscape, the following parameters can be defined in order to construct and assess point density needed for effectively defining ground sampling necessity (TABLE 2).

TABLE 2: POINT DENSITY VERSUS POINT DISTANCE IN LIDAR DATA (AFTER GOBAKKEN & NÆSSET, 2008)

ppsm	point distance (cm)	ppsm	point distance (cm)
0,1	316,23	2	70,71
0,2	223,61	3	57,74
0,3	182,57	4	50
0,4	158,11	5	44,72
0,5	141,42	6	40,82
0,6	129,1	7	37,8
0,7	119,52	8	35,36
0,8	111,8	9	33,33
0,9	105,41	10	31,62
1	100	16	25

The possibilities for information extraction from any interpolated DEM are therefore highly related to interpolation by ppsm, as is also revealed in FIGURE 12. Minimum ground sampling towards target geometries can be defined such as pitfall traps. Trier et al. (2011, 135) suggest a minimum of 1,8 ppsm to properly sample pitfall traps, but by a ground sampling that is already excluding vegetation and building returns, meaning an initial higher ppsm is needed for the initial scan. As suggested, this initial scan, especially for detection within densely vegetated areas, should be by acquisition resolution of 4 ppsm in order to be better capable of distinguishing between canopies and hidden or exposed archaeological monuments. This is especially needed for the detection of archaeological features smaller than pitfall traps, and increases the potential of visually manipulating unknown details hidden in the landscape. For the detection of burial mounds, similarly it would require c. 2 ppsm by point density of c. 0.7 cm. For already filtered data, a 1 m grid is a minimum necessity. Thus, a filtered dataset of 1 ppsm is sufficient for the detection of larger archaeological monuments in the landscape, but with some distortion of details while also omitting many smaller structures of potential interest. Most LIDAR products are, however, delivered in 1 m gridded planes, resulting in limited pattern detection possibilities. The optimal minimum solution would be 1.8 ppsm, and the best solution would be 4 ppsm as illustrated by investigations from the TLS study on the Königstuhl hillside in Heidelberg (Raun et al. 2018). But it is all dependent on context of landscape and necessary information extraction by the features and structures investigated. Bollandsås et al. (2012) also concluded that 1 ppsm did not make for sufficient detection of archaeological features in the landscape, and found that a significant increase in visual detection rate for archaeologist was evident by an increase to 5 ppsm. However, by an increase to 10 ppsm it was a less distinctive increase in detection by the test group (Bollandsås et al. 2012, 2742). Archaeological monuments such as burial mounds, pitfall traps, kilns, cairns, and monuments of a sizable extent and size will not have any trouble being visually detected in a 1 m gridded plane by 1 ppsm. The uncertainty of the point measured when the density become s less than 1 ppsm, however means, that the recorded information becomes uncertain to a degree where validation of terrain and surface becomes problematic for archaeological monument detection. Nonetheless, it is all dependent on the features and details intended to be detected, and thus amount of information required. Interestingly as well, is the impact of cognitive and semantic approach for human and computational vision. From Bollandsås et al. 2012, the detection rate and success was significantly different from test person to test person, meaning also a necessary consideration of human bias when interpreting the results of detection rates in LIDAR data, as well as by different interpolation by ppsm. Equally so, the detection rate and success differs by ppsm, as shown in the study of Trier et al 2011. However, from less points within and plane, to more points within a plane, does not result in linear increase of results. This was also the conclusions on the Königstuhl fieldwork (Raun et al. 2018). Thus, it is a matter of settling by finding best mean, which is given by 4 to 5 ppsm (Bolandsås et al. 2012, 2742; Raun et al. 2018).

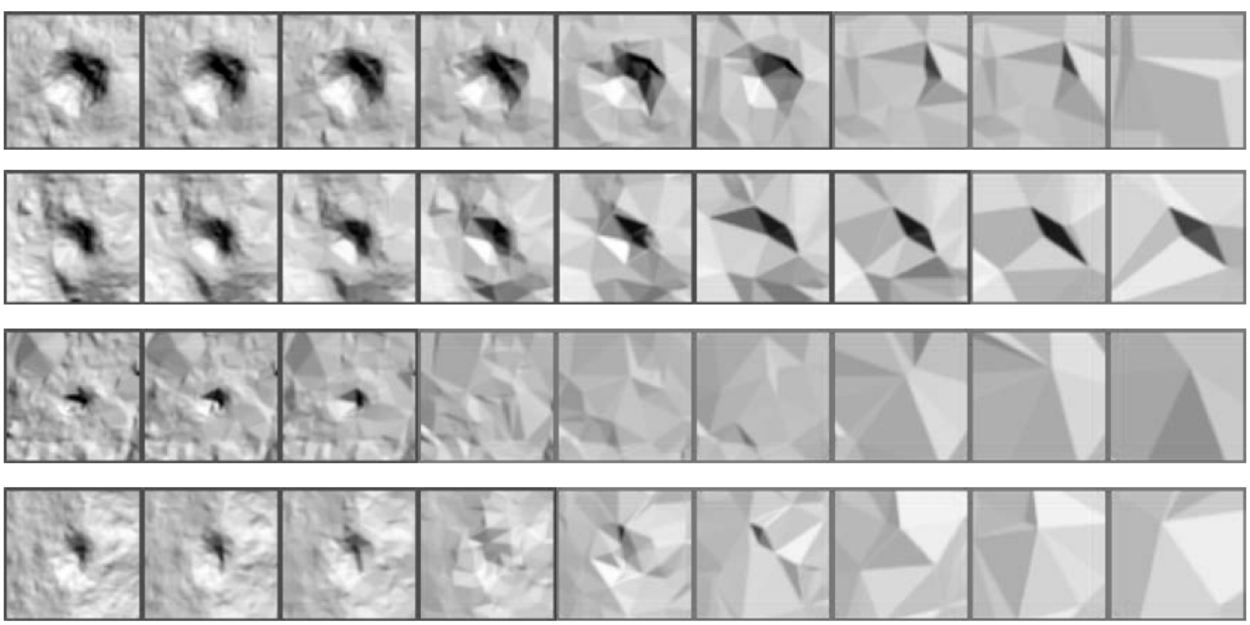

FIGURE 12: FOUR PITFALL TRAPS AT NINE DIFFERENT POINT DENSITIES. REDUCED DATASET BY PPSM FROM LEFT TO RIGHT IN DIFFERENT CONTEXT: 7.3, 3.6, 1.8, 0.73, 0.29, 0.15, 0.073, 0.036, AND 0.007 PPSM. THEY FOUND 1.8 PPSM TO BE NECESSARY FOR COMPUTATIONAL DETECTION OF PITFALL TRAPS (TRIER ET AL. 2011; TRIER & PILØ 2012)

2.10 LIDAR VISUALIZATION

LIDAR visualization is within the field of image analysis, and LIDAR visualization is an important part of post processing data for aiding human cognition and computational logic. This means that visualization of LIDAR data is key for both quantitative and qualitative studies, because it represents the visual aspects on how data should be read and understood, and how features and details are represented. DEMs are the representation of 3dimensional XYZ data on a Cartesian plane, with a gradient representation of Z as elevation. However, dependent on perspective and goals, different visualizations can be more informative than others. As such, there is no objective visualization of the digital landscape, but possibilities exist towards means of standardizing for data comparison to potentially make human and computational logic more objective. Without standardized approaches for pre-processing and processing LIDAR data from acquisition to data construction, any post-processing, or visualization, will not make sense. All steps are therefore necessary for making best practice recommendations for visualizing the digital landscapes of DEMs. The main questions for choosing how to visualize landscape, is therefore: How is data constructed? What is the context? And what is best suited to visualize the characteristics of features for information extraction? Data construction is answered by data acquisition, i.e. scanner and sensor model, nominal point density, nominal swath overlap, date of data. Context is defined by external conditions of landscape by topography, i.e. degree of slope, and morphology of features within. Lastly, information extraction by visualization is determined by the two former, as well as personal preferences for qualified studies and computational time for quantitative studies. This reasons the necessity of understanding all steps of LIDAR data from points to planes necessary to make large-scale investigations of landscape, and equally more so to document algorithmic procedures undertaken for the three individual steps of LIDAR data construction. The metadata construction for visualizations should include visualization technique and parameters used. Parameters change in accordance to technique, but as proposed by Kokalj & Hesse (2017, 39), some mandatory and ancillary parameters are necessary to document means of LIDAR visualization (TABLE 3).

TABLE 3: METADATA REQUIRED FOR DEM VISUALIZATIONS (AFTER KOKALJ & HESSE 2017, 39)

visualization technique	mandatory parameters	ancillary parameters
shaded relief	illumination azimuth	illumination elevation, vertical exaggeration factor, histogram stretch
slope	histogram stretch (min/max)	
trend removal and LRM	low pass filter radius	histogram stretch, color code, type of low pass filter
openness	positive/negative, greyscale/inverted greyscale, search radius	number of search directions, histogram stretch
sky-view factor	search radius	number of search directions, histogram stretch
local dominance	search radius	observer height, histogram stretch
cumulative visibility	search radius	observer/target height, angular resolution
accesibility		search radius, number of search directions
MSII	reference vector (if not zero)	number of scales, min & max radius, histogram stretch
Laplacian-of-Gaussian	filter radius	greyscale/inverted greyscale, histogram stretch

Changes in visualization by, for instance, change of azimuth and degree angle of illumination, radically changes human perception of landscape. Mounds look like pits, and degree of slopes less exaggerated, as can be seen in FIGURE 13 below. FIGURE 13a visualize contour lines, giving an indication of elevational changes within the plane. FIGURE 13b shows elevation by gradient, thus showing elevational levels making it distinguishable minimum and maximum values. While FIGURE 13c and FIGURE 13d gives relative elevational changes, making it possible to increase scale of perspective by comparison of information throughout the gradient scale. However, FIGURE 13c and FIGURE 13d shows the clear implication of change in azimuth and interpretation of positive or negative curvature within the landscape.

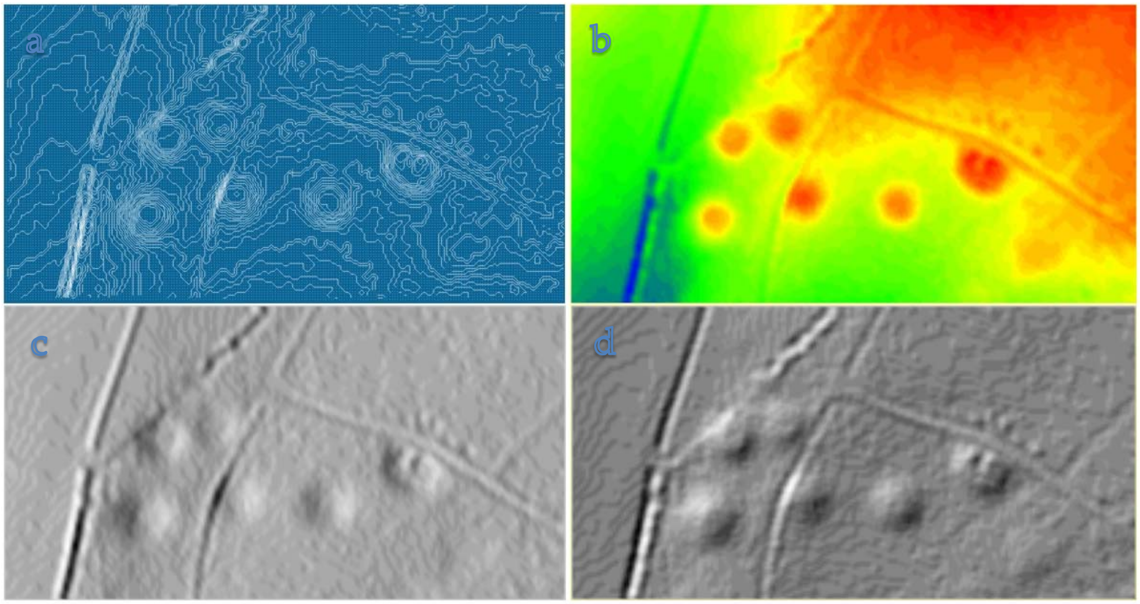

FIGURE 13: BURIAL MOUNDS FROM OBERHAUSEN. BY: A: CONTOUR LINES, B: ELEVATION MESH, C: SHADED RELIEF: 45° AND 90 DEGREE, D: SHADED RELIEF: ZENITH: 45°, AZIMUTH: 315°. © BVV.

Difference in means of visualizing landscape impact information extraction by visualization techniques, and thus highly impact the potential of archaeological feature detection. To some degree, this can be quantified towards applicability of techniques towards specific archaeological features, because the different techniques have different advantages in visualizing degree of slope, negative and positive elevation changes, flatness, steepness, or roughness. A determination of variation by applied visualization techniques can be referenced in Figure 14.

As a consequence, multiple perspectives are often necessary to complete a picture of the landscape and the features within. Areas directly facing the point of illumination, or opposite, are usually less detailed due to saturation levels being too extreme. Changes in azimuth can relieve this extreme saturation, or it can be solved by other visualization techniques that incorporate multiple illumination points towards one singular output, such as sky-view factor and openness. To locate correct parameters for target archaeological geometry in the landscape, experimentation is necessary, because where some visualization techniques offer improved visibility for certain details, it obscures the detection possibility of others. The most common visualization technique for archaeological detection is by relief shading of elevation differences, because it offers an intuitively readable visual impression of landscape (Kokalj & Hesse 2017, 16). Relief shading, or hillshade, offers an impression of a 3dimensional landscape on a 2dimensional plane – elevation differences seem natural for the human eye. From a computational point of view, this naturally is not similar, but still offers a normalized visual impression by which many different types of landscape can be compared by same standard. Shaded relief models are illuminated by a constant direct light from same azimuth and elevation angle. By very low illumination source angles, e.g. <10°**,** extremely subtle changes in elevation can be detected. This is especially useful when local areas need further exploration to reveal all hidden details in the landscape, but is not useful for large-scale investigations due to information also being lost by overlap and pattern overflow. The biggest problem with shaded relief models, as also demonstrated in FIGURE 13, is the direction of illumination. Archaeological features and structures that are not represented by linear patterns, do not present the same angular problem by illumination. For instance, burial mounds generally have curvature towards all angles, and therefore do not present a problem for relief shade models. However, linear patterns can be hidden within a visual representation by a single light source by running parallel with the illumination. Meaning, linear archaeological structures running parallel with the illumination source will not be visually represented due to the lack of relief shade (Devereux et al. 2008). In general, linear structures can be very problematic to detect in LIDAR data, i.e. by chance of point recording on both elevational positions towards correct interpolation, but also by visualization if multiple angles of relief shading is not being practiced. The detection of structures for archaeological mapping is therefore somewhat problematic because of the dangers of omitting details in the landscape when visually manipulating how the digital landscape is represented. To overcome some problems with singular dimensional representation, various techniques for visualizing DEMs have been created. Some techniques are created for more objective representation of landscape, while others intend to enhance the subtle changes of elevation in certain environments of landscape. As mentioned, for instance, linear structures running parallel with the illumination source, is not represented in singular hillshade models. For this reason Devereux et al. (2008) presented *Principal Component Analysis* (PCA) to visualize a correlation of 16 illumination directions to create a more objective representation of linear features within the landscape. *Sky-View Factor* (SVF), created by Kokalj et al. (2011), also tries to overcome the problems of linear detection by revealing negative curvature by a complete diffuse illumination from all angles. Similarly Hesse (2010) created a *Local Relief Model* (LRM) to represent local positive and negative elevation to enhance detection of subtle changes and simplify curvature. The Openness of a feature is equally interesting towards how to objectively represent landscape. Positive and negative Openness for archaeological LIDAR was created by Doneus (2013) to represent small elevational change, but distorts the possibilities of representing small and large curvature changes at the same time. Likewise Multi-Scale Integral Invariants (MSII), created by Mara et al. (2010), determines volume fractions for each DEM pixel, thus creating a single value for each pixel to indicate low or high neighboring value within a DEM for automated information extraction. All have unique characteristics of representing a digital surface and a digital landscape, but they all have different strengths and weaknesses. For the human cognitive understanding of landscape, the simple hillshade is still the preferred means of representation, but does not offer the full range of information within the DEM. However, the need for computational power for hillshade datasets are reduced compared to other techniques of LIDAR visualization. Meanwhile, the need for comprehensive analytical human cognition to understand relief visualization of the digital landscape by hillshade is lesser for the human interpreter. Given the popularity of hillshade representation of DEMs, and the relative ease of information extraction for archaeological purpose, hillshade models also represent a highly comparable and standard representation of elevational data. This can be a result of simple relief visualization of landscape not overcomplicating the procedures of processing and postprocessing data, and thus that the increased amount of use and large-scale comparison of data can enhance the quality of information by simple availability and readability. The concern therefore becomes whether or not the different visualization techniques, as e.g. shown in FIGURE 14, justifies a change of common representation of DEMs, or whether the standard should remain hillshade visualization with additional visualization techniques for target specific investigations. The main vizualisation of the repository of LIDAR data from Unerfranken later introduced, are produced as hillshaded visualization of a setting sun at 315° azimuth to represent this standardized visualization of landscape for both human and computational interpretation of landscape. Different visualizations for DEMs are produced and exemplified in chapter 5 by its comparative source for automated information extraction.

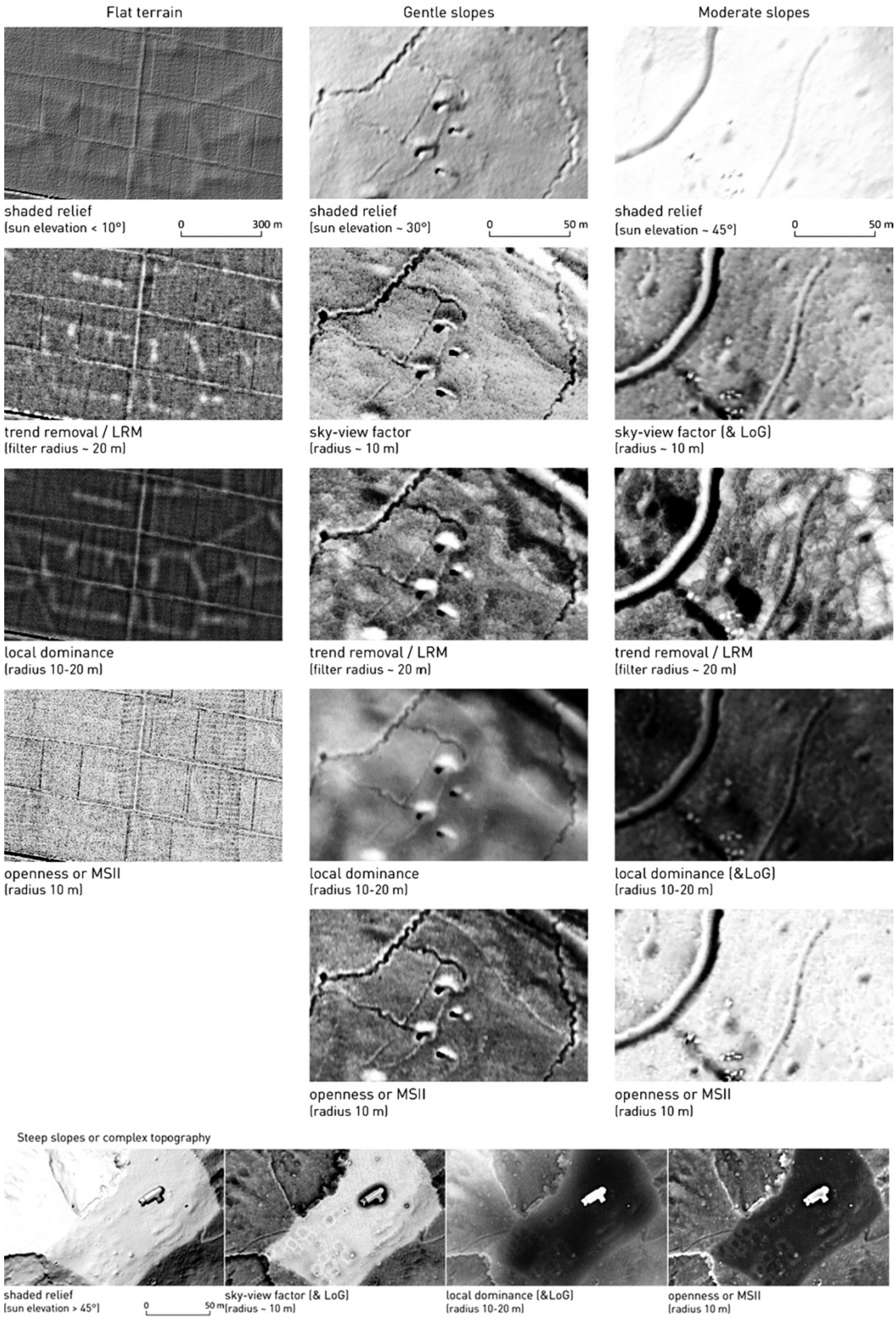
Flat terrain
Gentle slopes
Moderate slopes
shaded relief
(sun elevation < 10°)
0
300 m
shaded relief
(sun elevation ~ 30°)
0
50 m
shaded relief
(sun elevation ~ 45°)
0
50 m
trend removal / LRM
(filter radius ~ 20 m)
sky-view factor
(radius ~ 10 m)
sky-view factor (& LoG)
(radius ~ 10 m)
local dominance
(radius 10-20 m)
trend removal / LRM
(filter radius ~ 20 m)
trend removal / LRM
(filter radius ~ 20 m)
openness or MSII
(radius 10 m)
local dominance
(radius 10-20 m)
local dominance (&LoG)
(radius 10-20 m)
openness or MSII
(radius 10 m)
openness or MSII
(radius 10 m)
Steep slopes or complex topography
shaded relief
(sun elevation > 45°)
0
50 m
sky-view factor (& LoG)
(radius ~ 10 m)
local dominance (&LoG)
(radius 10-20 m)
openness or MSII
(radius 10 m)

FIGURE 14: VISUALIZATION TECHNIQUES ILLUSTRATING DIFFERENT FEATURES IN THE LANDSCAPE IN ACCORDANCE TO SLOPE. (FLATLANDS) PLOUGH HEADLANDS ON A FLAT PLAIN NEAR ENDINGEN AM KAISERSTUHL. 1 M LIDAR DATA © LGL IN BADEN-WÜRTTEMBERG. (GENTLE SLOPES) THREE DIFFERENT TYPES OF WORLD WAR I TRENCHES WITH SHELTERS ON GENTLE NE SLOPES OF ČRNI HRIBI, NEAR RENČE, SLOVENIA. 1 M LIDAR DATA © ARSO, SLOVENIA. (MODERATE SLOPES) CHARCOAL BURNING PLATFORMS IN THE HILLS OF THE BLACK FOREST. 1 M LIDAR DATA © LGL IN BADEN- WÜRTTEMBERG. (STEEP SLOPES) A LATE ROMAN CAMPO ON A ROCKY OUTCROP WITH A CHURCH OF ST. HELENA, WEST OF KOBARID, SLOVENIA. 0.5 M LIDAR DATA © WALKS OF PEACE IN THE SOČA RIVER FOUNDATION (KOKALJ & HESSE 2017, 36-7).

2.11 LIDAR ACCESS

The availability of remotely sensed data for archaeological investigation differs widely from country to country all around the world, and also within Europe. Some countries and regions offer publicly available remotely sensed data, whereas others adopt a business model for the availability of remotely sensed data, or simply restrict access. Especially in Germany this is well illustrated by the differentiated approach to public availability of LIDAR data. Two states out of 16 offer open free downloadable LIDAR data for public use as of spring 2017. The LIDAR archives are traditionally stored in the 16 state survey departments where requisition of LIDAR data requires larger investments for use and sharing under common license. However, more and more countries, states, regions, and municipalities are making remote sensing archives available to the general public on a European scale. This project is also a testament to the changing attitudes towards open data, as point clouds of Unterfranken in Germany were made available for scientific investigations as *XYZ* point clouds for the *Junior Research Group, Digital Humanities, Heidelberg University.* Advances towards open and freely available LIDAR data can also be seen by the increasing amount of international repositories and portals publicly available for use and download, e.g. OpenTopography, USGS Earth Explorer, Lidar Online, Open Access Hub, and many more. Open sources for global datasets are available for continental, national and regional studies by SRTM Global and ASTER Global DEMs, obtainable at earthexplorer.usgs.gov. The result of such initiatives impacts potential use by removing barriers of cost and time, and thus improves data quality. By the possibility of control comparison and added spatial information, new data will be enriched by already known information, and improve the scale of potential investigation. However, in situations where remotely sensed data is only publicly available by request or payments, cost by time and value, can directly halt projects of improvement or innovation. When a request for remotely sensed data is necessary, it slows down the process of acquisition for any project.

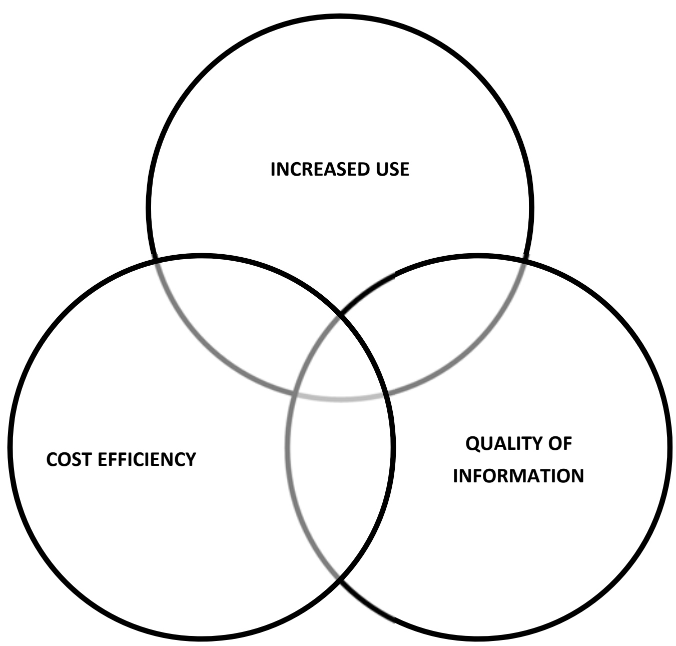

FIGURE 15: A SCHEMATIC DEPICTION OF KNOWLEDGE CONSTRUCTION

Consequently, this has a negative impact on the use of remotely sensed data, especially for archaeological investigations. Many archaeological investigations are based on small timescales for prospection, investigation, and interpretation. As a result, any formal administrative request could easily stop or slow the process of acquisition down to such a degree that remotely sensed data only becomes a means of visualization of information, rather than as a means of investigation. This limits the potential impact of remotely sensed data for archaeological investigations by removing a meta-layer of information for knowledge construction. By direct availability of remotely sensed data, such as airborne LIDAR, it increases the range of perspectives from singular entities to patterns, and from micro- to macro-scaled perspectives on the landscape and the past. Because, increased use by the community is controlled by time and cost efficiency. The end result is improved quality of information for both manual and automatic information extraction from digital landscapes by availability and scale of investigation. The structure is exemplified in the schematic depiction in Figure 15. The three pillars of knowledge construction will be a common theme throughout this thesis. Because, quality of information is not linear to rate of detection, but rather as a cost-benefit analysis by invested material cost and invested cost of time to impact quantity of use, and thus quality of information. Only by finding a balance between knowledge construction and remote information extraction, can we justly apply large-scale archaeological investigations of landscape.

2.12 LIDAR FORMATS

The LIDAR product is delivered in many different formats, but it all stems from three coordinates on a defined plane. Added data information can be added to the data string within one point in space, but it is still just a point in space by XYZ. Typically, the LIDAR product is delivered as gridded points in ASCII text files with internal separation or interpolated and rasterized DEMs, DSMs and DTMs as GeoTIFF container files for pixel determination of spatial extent by georeference. In the raw point cloud they can also be delivered in container files besides the ASCII text formats to standardize and compress data, such as LAS and LAS-extension files by binary compression, i.e. 2-base numeral system of 0 or 1. Container files, such as LAS files, incorporate the possibility of integrating the full waveform of LIDAR data with classification values by standardizing the classification of wavelength peaks, resulting in class 2 always classified as terrain and a range of classes for surface details. However, LAS classification extent changes accordingly to the level of detail available in the LIDAR data, and is therefore not a finite definition. But the ASPRS have set up a standard for classification within the file structure which follows much of the industrial standard of file exchange between producers and consumers for LIDAR data by classification of wavelength. Classification of wavelength will naturally be expanded, and therefore the data structure is not a finite product, but rather a guideline of extension. ASCII files are as equally transferable between systems as LAS files, if not more so by its simple construction of data as text, but ASCII files easily become a burden by sheer file-size compared to LAS formats by binary encoding. The LAS files are however, unreadable for the human eye due to the binary structure of data and thus some transparency of data can be lost in the compression procedure. LAS files are also changing towards more compressed LAS extensions, and the danger then becomes whether or not software producers are able to standardize capability of reading and handling new formats, or whether a division of file formats will arise. Thus, presently the best means of storing LIDAR data can be argued to be by Unicode characters in ASCII files by data separation, e.g. comma separated values, csv. For working with LIDAR data, a transformation and compression of data to LAS extensions can be needed for handling and working with large-scale LIDAR projects.

However, LIDAR data is delivered in many file formats, and will continue to do so as the field develops. The key aspect is maintaining separation of individual recorded values, and making sure that LIDAR data remains open by not creating restriction by compression and encryption of data to locked market specific standards. Restraining access by data encryption is a slippery slope, because it is a sought after control to safeguard datasets from being freely used without purchased rights of access and publication possibility. Such processes tends to halt use more than safeguard the potential misuse and control of data. This results in some file formats being constructed towards only being available by certain software possibilities. Naturally, there are abundances of file formats for containing LIDAR data and LIDAR metadata. Similarly so, there is an abundance of container files for interpolated raster that are build towards specific tasks and means of reading data by target programming languages or to coordinate with other datasets. This is a valid necessity to structure data, but an abundance of container files for both LIDAR points clouds and interpolated LIDAR raster, limits efficiency and potential quality of information by a lack of possible use across platforms. The potential of LIDAR in archaeology by both the professional and layperson community, can therefore be somewhat complicated by this dilemma. That is why keeping the data as ASCII text files by comma separated values for LIDAR data, can be the simplest and most long term solution for transferring and storing point cloud information, but not the best solution for minimizing data file size or computational procedures. However, for much of the archaeological community, it is the already interpolated raster as GeoTIFF files that are delivered. GeoTIFFs have a general widespread use within all fields, and serves as an interface for gridded space in compressed and decompressed formats. Equally more so, the added spatial record gives the possibility of transferring coordinate structure on a Cartesian plane across most platforms and software solutions. This leads to TIFF files in general being the most recommend file format for applications and storage, and GeoTIFFs being one of the most used formats for remote sensing.

2.13 ARCHAEOLOGICAL LIDAR POTENTIAL

The archaeological potential of LIDAR data is founded in its ability to depict dimensions, and equally more so to add dimensions to the possibilities of interpreting the cultural landscape. By its natural 3dimensional space, spatial understanding plays a large part on information extraction from the landscape, and archaeological monuments become visual representations by elevational change. The potential of archaeological LIDAR is also by its documentation scale from structures to sites by TLS, and from local areas to international and worldwide comparison by ALS. Borders do not intrinsically exist in LIDAR data, and landscape can therefore be better perceived as a connected landscape by all its revealed information of natural and cultural traces and patterns. LIDAR is a digital product, and can therefore be manipulated to visualize certain details. The use of LIDAR to manipulate the digital landscape to segment categories of terrain, surface, and potentially everything in between, is undoubtedly the strongest advantage of LIDAR data. But it is not the only advantage. LIDAR data aid investigating spatial integrity of monuments and landscape by spectral values and geometrical composition by keeping a physical measurable record of information to reference the changes in landscape of human and natural impact. By the simple detection of change between two datasets of point clouds, recorded at different time intervals, it is possible to see changes made in the landscape, e.g. by modern construction, farming, and foresting impact on landscape (Walter 2004). This offers a simple large-scale possibility of cultural heritage management. However, in order to be effective, data from both sequences needs to be standardized and correlated to be comparable. This means that same standards of geometric and radiometric calibration towards regulated benchmarking data are necessary; otherwise the systematic errors can skew data to such a degree that direct comparison is not possible because of inconsistencies between the datasets. However, the same point is never measured again in LIDAR data, because it is random large-scale light emission. This can be compensated by the gridding of points into one point per square meter to represent the mean of all recorded points, resulting in some changes of elevational accuracy being inevitable. Gridding to mean is more necessary when the densities of point sampling are smaller, i.e. by ALS scanning in certain altitude above earth, compared to the denser point sampling by TLS. Equally more so, measuring terrain and surface by different bands in different wavelengths increase the possibilities of segmentation and classification of the landscape by multiple variables. But what is continually necessary, is to construct data given. In most archaeological situations, the case rarely constitute densely distributed measurement points of light in different wavelengths, but rather scarce point sampling of discrete return of first and last pulse of the landscape. This is by no means a disadvantage, and is still of great value for landscape interpretation, almost no matter the point sampling density of LIDAR data. However, with lower density sampling, interpolation plays a more significant role for the representation of continued or abrupt changes of elevation. Meaning that especially for DEMs with low density sampling, substantial focus is required on the means of post-processing point clouds of interpolation and image analysis for manual and automatic extraction in order to retrieve the largest amount of information for archaeological mapping. Otherwise, the ratio between detecting true positives and false positives will be unequally distributed, and true positive detection remain uncertain due to details lost by misclassification or lack of classification by remote investigations. For remote investigations of landscape, a certain degree of ground trothing and verification will always be a necessity for most investigations. The biggest potential of LIDAR data is therefore not necessarily in its potential of application for singular perspectives, but rather by its wider application as perspectives and altered perspectivesby both professionals and laypersons for the construction of qualified knowledge by comparative use. Applying simple large-scale algorithms for the detection and segmentation of archaeological monuments in LIDAR data is interesting for questions regarding efficient use towards constructing improved knowledge production. This should be understood by the increase in an increased user domain being able to add other sources of information for landscape investigation by formulating quantified and qualified conclusions based on the details detected in landscape. However, does this lead to improved quality of information or simply improved quantity of information? To see the potential of archaeological monument extraction from LIDAR data, we therefore need to evaluate the use and impact of semi-automated information extraction for qualitative and quantitative assesment. In **chapter 3**, **LANDSCAPE PERSPECTIVES,** primary data is introduced, and the field of automatic archaeological monument detection is qualitatively assessed. The use and impact of automated and semi-automatic information extraction, is analyzed, visualized and modelled in chapter 4, **STATE OF AUTOMATED AND SEMI-AUTOMATED DETECTION IN REMOTE SENSING ARCHAEOLOGY,** in order to quantitatively asses state of the field and define best practice. In chapter 5, **APPLIED DETECTION IN LIDAR DATA,** pattern recognition will be assessed, and adapted to show human and computational interpretation of digital LIDAR landscapes. This will all be summarized and assessed in chapter 6, **CONCLUSIONS AND PERSPECTIVES.**

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3. LANDSCAPE PERSPECTIVES

The landscape, as terrain and surface, consist of many details that visualize past human presence. To determine cultural or natural impact on landscape is a difficult assertion when based on singular entities. On macro scale, landscape is a homogenous construct influenced by heterogeneous events of both cultural and natural impact. Patterns in the landscape can show source by different perspectives and scales. Thus, interpreting landscape requires a necessity of scaled pattern investigation of artificial constructs in the landscape as true or false entities. The patterns of archaeological monuments are represented in shapes of elevational difference within LIDAR data, and all detectable entities within LIDAR data are elevational change in relation to the natural curvature of landscape. However, the distinction between cultural and natural landscape can be somewhat arbitrary, since remains of the past are slowly integrated into the terrain by decomposition and decay. Observed distribution therefore need careful consideration compared to strategies of data collection and transformation of the landscape (Cowley 2016, 148). Emerging patterns can be a result of missing as well as missed observation and registration. In many instances it is a case of training how to interpret the landscape, and thus code both the computer and the human mind to look for certain distinctive details in the landscape by micro or macro patterns. Details are easily subconsciously ignored if they do not fit the expectations (Halliday 2013), and both the human and computational interpreter can create gaps of information if not properly trained or adapted.

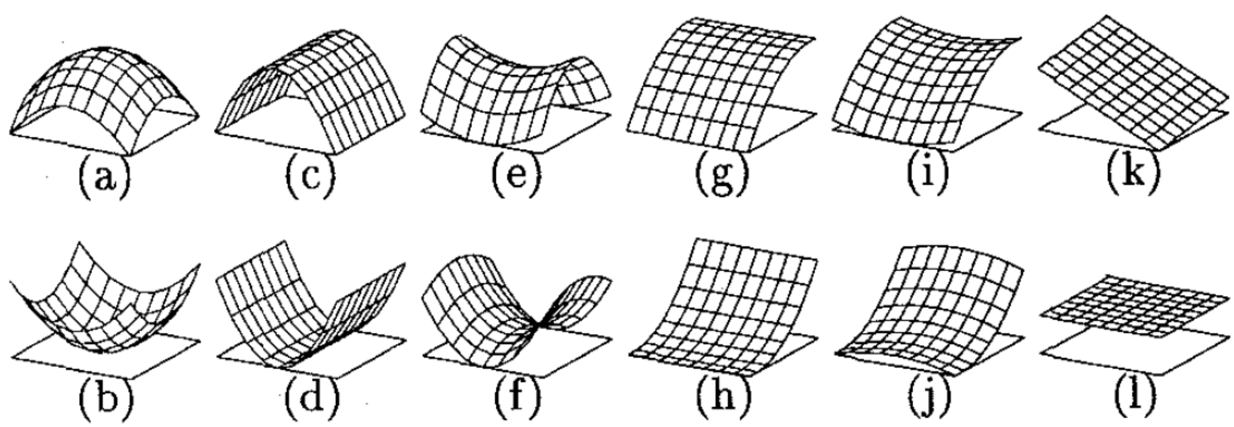

FIGURE 16: CURVES IN THE LANDSCAPE. **(A)** PEAK; **(B)** PIT; **(C)** RIDGE; **(D)** RAVINE; **(E)** RIDGE SADDLE; **(F)** RAVINE SADDLE; **(G)** CONVEX HILL; **(H)** CONCAVE HILL; **(I)** CONVEX SADDLE HILL; **(J)** CONCAVE SADDLE HILL; **(K)** SLOPE HILL; **(I)** FLAT (TRIER ET AL. 1995, 924).

The complex pattern of archaeological data means that singular perspectives creates bias between past and present patterns, resulting in omission of unknown patterns of the past and present. Because, the geometrical patterns in the landscape are constructed by both cultural and natural influence, resulting in curvatures having a wide range of origin points, but potential visual presence in a range of curvatures (Figure 16). The range of curvatures by peaks can for instance fit both natural and cultural origin points, causing singular curvatures fitting multiple classifications, and thus minimize potential impact of comprehensive interpretation of areas of interest within a given landscape.

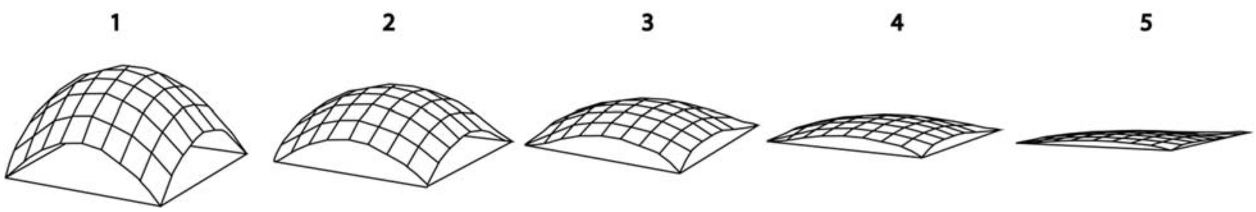

FIGURE 17: IDEALISED VERSION OF GRADUAL DECAY OF PEAKS BY WEAR AND TEAR

All curvature and height adjustment in the landscape has a range of natural and cultural influencers. A peak can be the accumulation of debris from both natural and cultural origin, but can also be constructed peaks because of specific actions and intentions, e.g. sedimentary movement or placement. Equally, peaks in the landscape, such as burial mounds, are affected by wear and tear through time by weather, erosion and living things changing original shape by displacement. Displacement and removal of materials decreases size and presence of curvature in the landscape, and thus slowly alters unique characteristics of cultural heritage monuments in the landscape, as exemplified in FIGURE 17. All peaks show some degree of decay by the displacement of materials from original or prime shape, but especially artificial mounds are on a gradual scale from original shapes towards integrated into terrain as flat landscape, such as in cultivated agricultural soil. Likewise, ridges can be constructs of cultural landscape manipulation, but also natural changes of erosion and isostatic equilibrium of height adjustments from the dynamic buoyancy of sediments. Thus, geometrical features and simple shapes are created by a wide range of processes. Meaning the curvature can be interpreted by a cultural origin point, such as: a peak understood as a burial mound or waste accumulation; a ridge understood as wall or terrace origin; a pit understood as dugout for materials, waster pit or pit fall trap, etc.. They are all difficult interpretations when based on singular variables to use for the detection of archaeological monuments. Pattern recognition of archaeological monuments by remote sensing requires scaled perspectives to see individual or clustered patterns in order to determine cultural or natural origin. Overall pattern determines whether the point of origin is natural or cultural, and whether clustering is intentional or random.

However, the overall pattern is only detected if the individual geometrical shapes are initial segmented and extracted, resulting in the necessity of both micro and macro scale. Therefore, information extraction of singular variables do not complete the picture, but it makes for large-scale pattern detection to determine curvature in the landscape as potential natural or cultural origin. Thus, micro detection of the smallest unit within the frame makes for macro interpretation of cultural heritage. The patterns of cultural heritage, is patterned and ordered, because, humans are, and will always be, structured beings. However, humans are not simply overarching logical-thinking individuals, but humans are at the basis controlled by logical relationships between survival and social convention. Thereby not saying that humans are necessarily following social convention, but simply equally reacting to impulses and instincts in different contextual scenarios depending on the individual experience of cultural backgrounds. Humans are therefore illogical compared to what could be the best possible solution in various situations as rational logical cognition can and will be influenced by emotions (Tomasello 1999). That does not mean that emotions are not logical, but emotions can get in the way of what might be most rational. Human actors must not for these reasons, neither be degraded or exalted, because humans are not simply conscious or unconscious actors, but rather a little bit of both (Bourdieu 1977; 1998; Lakoff & Johnson 2003; Lévi-Strauss 1969). Praxis is therefore patterned and structured, even though individual thought and experience distorts, but never beyond the context of structure.

3.1 A PERSPECTIVE FROM LOWER FRANCONIA

For the applied means of information extraction from LIDAR data, a dataset has been constructed to further investigate the possibilities of semi-automatic and automatic large-scale archaeological information extraction. The primary target area for investigation and assessment is Lower Franconia, Germany (Figure 18). The dataset consist of a gridded LIDAR point cloud from Lower Franconia, comprising some 8544 km^2 LIDAR data from the state of Bavaria. In some areas, the laser scanning is documenting outside of the bounds of Lower Franconia, hence the LIDAR dataset is slightly larger in km^2 compared to the actual bounds of the administrative district of Lower Franconia.

The dataset specifications are: grid width of 1 m, ≤ 0.2 m height accuracy, and ± 0.5 m positional accuracy. The dataset constitutes of first and last echoes, structured as a binary-1 meter grid in the elevational reference system of DHHN92. Digital Elevation Models in Bayern have been instigated since 1996 by airborne LIDAR investigations, and is continuously updated and completed with new airborne scanning campaigns. For the area of Lower Franconia the dataset is complete and available for acquisition in a number of grid formats from the Bavarian State Offices for Sites and Monuments.

FIGURE 18: AREA OF INTEREST, LOWER FRANCONIA, WITHIN THE STATE OF BAVARIA. © OPENSTREETMAP CONTRIBUTORS

The point cloud used is structured for Lower Franconia by a 1 m grid width as a DEM1 or DGM1, *Digital Elevation Model* and *Digital Ground Model* respectively. This is nationally referred to as DHM1, *Digitales Höhenmodell* in a 1 m grid. The point cloud dataset is stored in a secure repository in the Integrated Rule-Oriented Data System, *iRODS*, to facilitate primary data management and secure data collaboration. The data is stored as separated XYZ ASCII text files to insure data readability and data sustainability across platforms and projects. The point clouds are stored as first and last pulses segmenting between surface and terrain. Equally, a combined dataset exist with both surface and terrain. The interpolated dataset for Lower Franconia is stored on Heidelberg University servers for collaborative research at the Cluster of Excellence, Asia and Europe in a Global Context. The interpolated LIDAR raster data are stored in GeoTIFF container files to keep pixel determination of spatial extent by georeference. The coordinating reference system is set on the Cartesian plane of a Transverse Mercator projection in Gauss-Krüger, zone 4, EPSG: 31468. Interpolation and visualization of the entire dataset was done in OPALS, *Orientation and Processing of Airborne Laser Scanning data* (cf. Mandlburger et al. 2009; Pfeifer et al. 2014). OPALS is a modular programming system consisting of components clustered thematically in terms of packages for specific application by point cloud data, especially oriented towards macro scaled perspectives of airborne LIDAR. The processing language for OPALS is simple and structured, allowing for large datasets to be processed and keeping spatial reference. The dataset was constructed by commands from a scripted batch file between the operating system and the OPALS processing program. The following script allows for tasks of repetition on segmented terrain point clouds to be converted into rectangular interpolated DEMs by the grid module. The derived grid model is stored in "pixel is point" interpretation, i.e. the grid values represent the interpolated heights at the pixel center instead of “pixel is area” where the raster value is valid for the entire cell area and not only for the center of the pixel. The script used for the dataset is fixed on three commands: Defining input to *OPALS data manager*, ODM, processing input, and constructing output (TABLE 4)

TABLE 4: OPALS CODE USED FOR INTERPOLATION

```

ODM container for calculation of XYZ input
opalsImport -inFile 1234_1234.xyz -outFile 1234_1234_xyz.odm -iformat xyz

Compute interpolation grid
opalsGrid -inFile 1234_1234_xyz.odm -outFile 1234_1234_dtm1.tif -grid 1.0

Generate relief shade visualization
opalsShade -infile 1234_1234_dtm1.tif

```

File name is exemplified by 1234_1234, as 4 x 4 digits optimal for the coordinate reference system of the narrow Cartesian plane of Gauss-Krüger, zone 4. From OPALS, data is interpolated to DEMs of 1 m cell size by same coordinate value as input. Grayscaled shaded relief is the visualization used for interpolation due to computational efficiency, as well as its data readability for information extraction by a human interpreter. Other techniques of visualization can be more useful for information extraction, especially linear detection (Kokalj & Hesse 2017, 35), but requires more computation and does not offer easy clarification for the inexperienced human interpreter. From the basic OPALS ODM structure, several possibilities of pixel transformation for a Z value can be calculated, such as by a *moving planes* interpolation (TABLE 5).

TABLE 5: Z-VALUE ADDITION BY MOVING PLANES CALCULATION

```

Compute grid by moving planes
opalsGrid -inFile 1234_1234_xyz.odm -outFile 1234_1234_grid_1m.tif -grid 1.0 -interpol movingPlane

```

Calculation of Z values offers several possibilities of transformation by elevation, slope, density, and exposition through the moving planes interpolation. Moving planes calculates for each grid cell *n* nearest neighbor points are queried and a best fitting tilted plane is estimated. The height of the resulting plane at the grid point of a XY position is mapped to the grid cell. The tilted plane interpolator allows the derivation of slope measures by: *n* of x, *n* of y, slope, and exposition for each grid point. Moving plane interpolation requires the specification of the number of neighbor points considered for interpolation of a single grid. The results of the neighbor queries can be restricted to a maximum search radius around the grid point, enabling a consideration in areas with sparse point density in the resulting grid as void pixels. This helps define areas void of pixels in the end product, but also a means of visualizing landscape according to different values of elevation, slope, density, and exposition. See TABLE 6 for a list of calculations of Z values.

TABLE 6: CALCULATIONS OF Z VALUES DERIVED SIMULTANEOUSLY AS SIDE PRODUCTS OF GRID INTERPOLATION

command	**parameter calculation**
sigmaz	*S* of interpolated grid height
sigma0	*S* of the unit weight observation
density	point density estimate
excentricity	distance grid point - center of gravity of data points
slope	steepest slope in percent
slpDeg	steepest slope in degree
slpRad	steepest slope in radians
slope	steepest slope in percent
exposition	slope aspect [rad] = azimuth of steepest slope line, N=0, clockwise sense of rotation
normal	x-component of the surface normal unit vector
normaly	y-component of the surface normal unit vector

Dependent on landscape, and details of investigation, Z value manipulation aids potential information extraction and archaeological monument extraction. Below it is exemplified by sigmaz by standard deviation of interpolated grid height to highlight more pronounced height changes (FIGURE 19). The entire dataset is built to incorporate Z value change and manipulation simultaneously with interpolation and visualization in OPALS, making it easy to change perspectives on landscape.

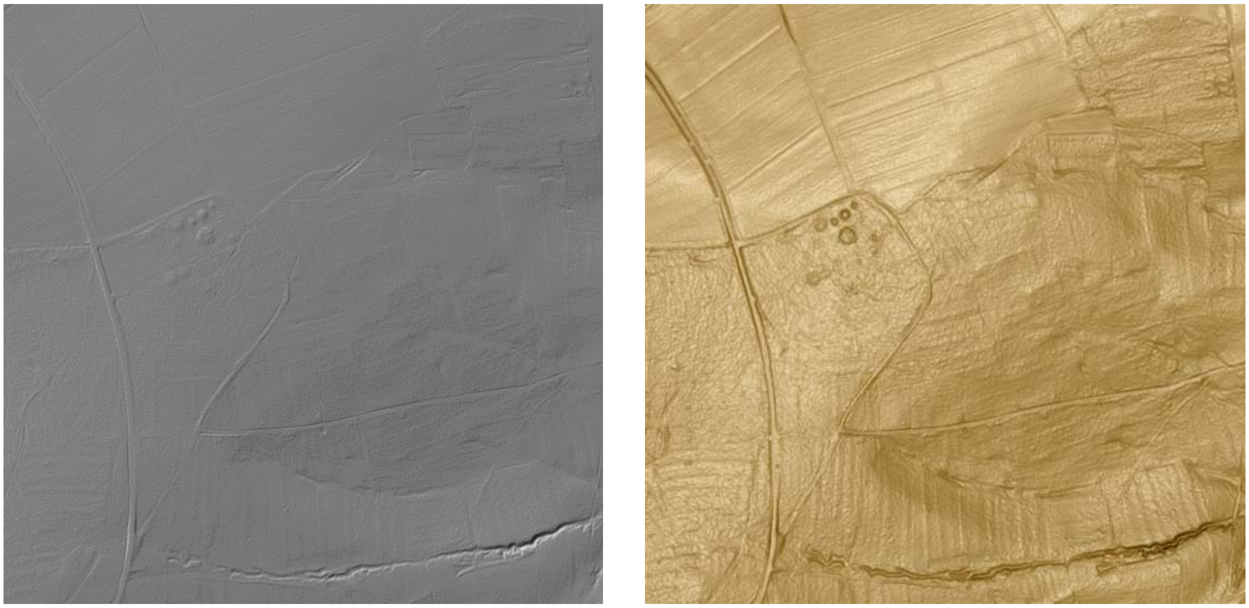

FIGURE 19: RELIEF SHADING TO HEIGHT CHANGES FROM RIEDENHEIM, LOWER FRANCONIA. THE AREA INCLUDES 11 BURIAL MOUNDS. SHADED RELIEF AND ZIGMA OF Z VALUE BY MOVING PLANES CALCULATION: AZI. 45°, 270 ANGLE: 1 KM2 TILE, ↑ NORTH

The complete dataset from Lower Franconia, consist of 9752 tiles of ≤ 1 km^2 georeferenced raster files in a GeoTIFF format. The complete dataset, histogram stretched to full dataset, can be seen in Figure 16 below, ranging from Gauss-Krüger, zone 4, coordinates of 4279000-5549000 to 4425000-5556000.

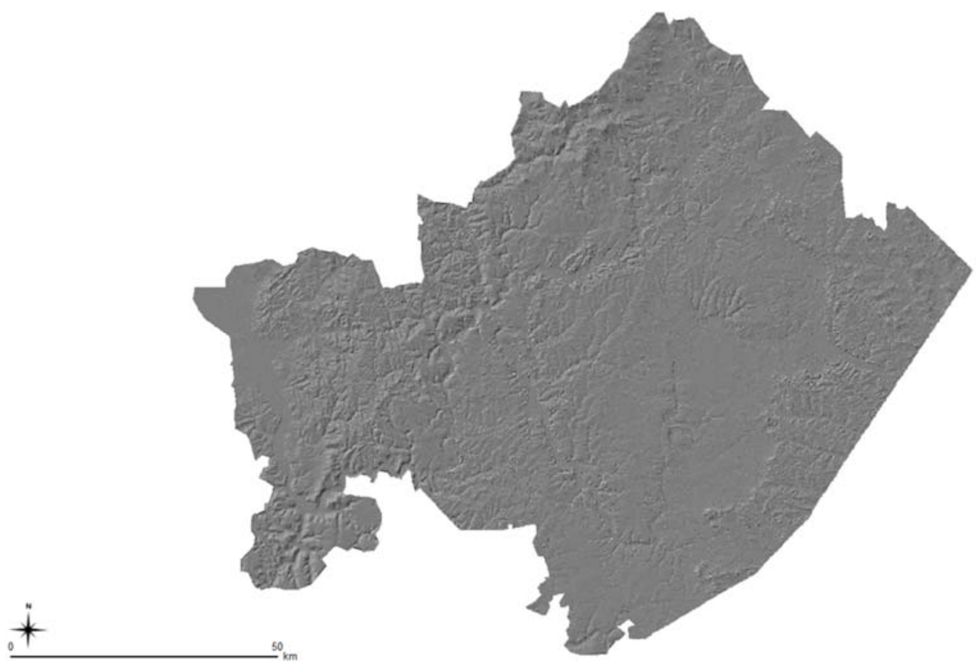

FIGURE 20: COMPLETE DIGITAL TERRAIN MODEL OF LOWER FRANCONIA BY SHADED RELIEF: AZI. 45°, 270 ANGLE

3.2 CASE STUDY ON SHAPE DETECTION: BURIAL MOUNDS

To investigate the possibilities of automatic detection for archaeological monuments within LIDAR data, nine sites in Lower Franconia have been selected for comparison and analysis (FIGURE 21; see also appendix 3B). For automatic detection, the case studies will focus on shape detection by burial mounds. The nine sites are all cultural landscapes of the past, and all contain burial mounds to a smaller or larger extent for scale comparison of quality by manual and automated detection.

FIGURE 21: SPATIAL COMPOSITION IN LOWER FRANCONIA OF THE NINE SITES FOR FURTHER INVESTIGATION

The nine sites have been explored by survey and remote investigation. The remote investigation is carried out by sampling known ground-truth, and new areas to explore by human and computational interpretation of landscape. Fieldwork was eplored after first initial sampling of known data, with different perspectives by expert human interpretationers and computational detection of areas of interest. The survey was carried out to determine ground truth of archaeological monuments detected or not detected by visual manual interpretation and automated computational interpretation. Both true, uncertain, and false positive detection were re-investigated by field survey. However, the end result is only best possible estimation by many different actors, and especially completely undetectable monuments by lack of any change in terrain compared to natural terrain, are impossible to determine and verify without archaeological excavation. Lower Franconia is rich in cultural heritage with many archaeological monuments still present in the landscape, but the investigation has focused on a "simple" shape detection by burial mounds. Burial mounds have an impact on the modern terrain of Lower Franconia as cultural peaks changing the natural curvature of landscape (see distribution in FIGURE 22). 860 locations are registered as sites containing one or more burial mounds at each location within Lower Franconia. The tumuli grounds are recorded as one point or area containing an unknown amount of graves and burial mounds, but define the base of potential information extraction for a complete picture of burial mounds within the LIDAR data.

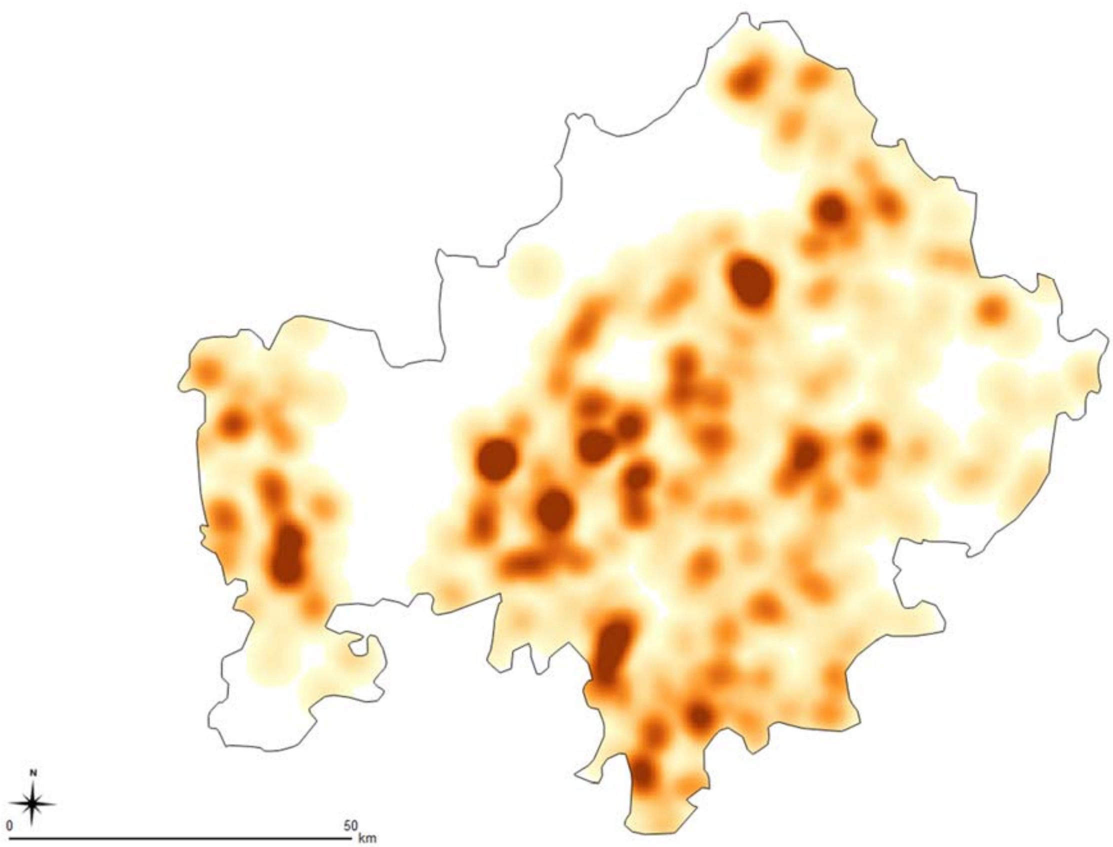

FIGURE 22: BURIAL MOUND CONCENTRATIONS BY KERNEL DENSITY DISTRIBUTION IN LOWER FRANCONIA

The burial mounds of Lower Franconia are located in a wide variety of landscape. In both flat and sloped terrain, in forested and open landscape. Equal to all remnants of the past, they are endangered and exposed to destruction by modern construction, as well as terrain and surface cultivation and extraction. This is not necessarily altered by whether or not the cultural traces of the past exist as known or unknown remnants in the landscape, because information can be difficult to assess when required to be actively mediated from heritage agencies. Accessibility to best possible mapping of cultural heritage is required to change the burden of active mediation of information from agencies to active information collection by agents. A complete mapping of cultural heritage in the landscape, both hidden and revealed, is impossible. However, known information should be easily accessible to help secure cultural heritage in the landscape from misguided and unaware destruction by construction and landscape cultivation. Presently the cultural monument record is partly revealed in Lower Franconia by macro scaled site registration. This is best practice for many parts of the world, but also results in unaware decisions based on misguided and lacking information. A necessity of archaeological mapping of monuments in the landscape is therefore of utmost importance, but it requires quantitative perspectives rather than qualitative narratives. Equally, quality of information is better exposed and revealed if understood by both micro and macro perspectives by more comprehensive depiction of the cultural landscape shaped by the past and present. Equally so, repetition and quantitative depiction and extraction is important to continued management of archaeological monuments in the landscape. For this purpose, computational detection from LIDAR data offers standardized and comparable results by data and model driven approaches of information extraction for change detection (Murakami 1999; Richter et al. 2013; Teo & Shih 2013; Walter 2004). However, this requires multiple datasets of comparability. In many instances, it is the initial documentation that is the main concern for further development, and for future tracking of change detection. To complete the picture, extensive mapping is necessary. However, the results are sometimes ambiguous and indiscernible. Meaning, it can be difficult to distinguish what results and conclusions are based upon, resulting in repetition being impossible. However, the necessity for verification and substantiating qualitative to quantitative investigation requires possibilities of replication. The nine selected sites for this study, follows similar practice outline in order to substantiate the qualitative information and micro patterns to quantitative replication and macro patterns. The examples given at the nine different sample sites, range from singular to numerous clustered burial mounds. They are located in flat as well as rough and sloped terrain, but all within areas less affected by human exploitation and situated in areas of vegetation. Some are in dense and unmaintained forest, while others are in more open production woodlands and plantations. Thus, the aim of subdividing segments of landscape for cultural heritage detection will be applied in a variety of landscapes and curvatures to see the impact on confidence values and detection results. The nine sites are presented in TABLE 7 and TABLE 8.

TABLE 7: SITE OVERVIEW WITH GROUND TRUTH ESTIMATE OF BURIAL MOUNDS WITHIN THE VICINITY

No.	SITE	Ground truth estimate of BM
1	**Stockstadt am Main**	12
2	**Triefenstein**	25
3	**Hohe Wart**	1
4	**Amorbach**	1
5	**Kleinlangheim**	26
6	**Riedenheim**	11
7	**Maroldsweisach**	10
8	**Stettfeld**	2
9	**Alzenau**	20

TABLE 8: DESCRIPTION OF INDIVIDUAL SITES

NAME	**Stockstadt am Main**
Description	Burial mounds; three clusters
Temporal or cultural frame	Unknown prehistory
Ground truth estimate	12
Nearest administrative UID	207688
File number	D-6-6020-0087
Sub district	361
12 burial mounds were located by field inspection. The 12 burial mounds are located in three distinct clusters, C1-3, but all are placed on the ridge towards the valley to the south. The burial mounds to the east, C1, are all heavily damaged by looting and a road running through one of them. All mounds in C1 are larger. The burial mounds in C2 are almost not noticable in the field due to canopy obstrcution, but stands out as patterns of clear cultural certainty within the DEM. The last cluster, C3, are quite prominent in the DEM as well as in the landscape, but all have also been looted at some point in time.	
NAME	**Triefenstein**
Description	Burial mounds; three clusters
Temporal or cultural frame	Unknown prehistory
Ground truth estimate	25
Nearest administrative UID	199043; 208622; 982209
File number	D-6-6223-0013; D-6-6223-0012; D-6-6223-0049
Sub district	613
Three distinct clusters of burial mounds, all located on the same plateau above the river Main, near Urphar. C1 consist of four flat topped burial mounds. C2 consist of minimum 11 burial mounds with some being cut by a pathway. Within the centre of the concentration the burial mounds are overlapping eachother, but it is difficult to assess stratigraphic relations without formal excavation. However, it does seem like the two burial mounds in the centre are the primary connectors. In between C2 and C3, some smaller circular earthenwork are also present as potential burial mounds, but they are all connected to the forest roads, and therefore might as well be connected to general earthenwork construction due to logistic patterns of waste dispersal. The last group C3, consist of a minimum of eight burial mounds of varying size, and are stratigraphicly overlapping. The temporal scope of the grave fields are undocumented, but a connection to the Migration Age fortification of Wettenburg is likely due to spatial presence within close vicinity.	

NAME	**Hohe Wart**
Description	Burial mound; one cluster
Temporal or cultural frame	Unknown prehistory
Ground truth estimate	1
Nearest administrative UID	977096
File number	D-6-6021-0094
Sub district	406

The burial mound of Hohe Wart, is a singular regocnisable mound located on a very steep slope on a hillside facing the north. By its physical presence, it stands out as a compact earthenwork covered with stones.

NAME	**Amorbach**
Description	Burial mound; one cluster
Timeframe	Unknown prehistory
Ground truth estimate	1
Nearest administrative UID	201173
File number	D-6-6321-0004
Sub district	470

The burial mound of Amorbach lies singuarly near the highest topographic point in the landscape. Forestry is very active, and fresh tractor tracks were seen dug into the side of the burial mound.

NAME	**Kleinlangheim**
Description	Burial mounds; one cluster
Timeframe	Hallstatt Culture
Ground truth estimate	26
Nearest administrative UID	209040
File number	D-6-6227-0058
Sub district	1154;1142

One large cluster of burial mounds with different degrees of preservation. Some older, and some more modern evidence of looting and digging in the landscape. West of the burial mound concentration, several potential overploughed burial mounds were identified due to slight elevation, and the discovery of ceramics of potential Hallstat Culture. Other finds of Hallstat Culture has been located in the vicinity, and is a likely connection to the burial mounds. The burial mounds are located in the small valley, almost at the lowest point in the vicinity, but with slight elevation towards the south.

NAME	**Riedenheim**
Description	Burial mounds; one cluster
Temporal or cultural frame	Unknown prehistory
Ground truth estimate	11
Nearest administrative UID	202035
File number	D-6-6425-0062
Sub district	774;768

Burial mounds of various degree of destruction and deteriation. However, most of them seem undisturbed from looting. There are two spatial placements of burial mounds at the site within two clusters. The first cluster is situated along the northern ridge of the forest. The second cluster is a little further inside the forest. In between the clusters is an empty area devoid of mounds, but with a hollow road passing through. The road is of modern use, but likely extends back in time as primary road in the area.

NAME	**Maroldsweisach**
Description	Burial mounds; two clusters

Temporal or cultural frame	Unknown prehistory
Ground truth estimate	10
Nearest administrative UID	134142; 132787; 132795; 132783
File number	D-6-5829-0008;D-6-5829-0012-4
Sub district	2138; 2138;2223
Dispersed pattern of individual and clustered groups of burial mounds on the slopes and plateaus of the landscape. In C1, one burial mound has since the LIDAR scanning been removed, and is no longer possible to locate in the field. The two others still present were large flat topped burial mounds. From C2 a dispersed pattern of burial mounds are seen. From the field investigation, the cluster of burial mounds were clear, and the two outer mounds also very likely prehistoric.	
NAME	**Stettfeld**
Description	Burial mounds; one cluster
Temporal or cultural frame	Unknown prehistory
Ground truth estimate	2
Nearest administrative UID	181267; 134234
File number	D-4-6030-0023; D-6-6030-0005
Sub district	994;2291
Two very centrally placed burial mounds on top of natural elevation. Both peaks of the Spitzlberg, have been in use for different purposes throughout time, and have been heavily shaped and destroyed by human activity. The western burial mound has been re-used as a new sarcophagus religious display, whereas the eastern mound has almost been completely hollowed out. Both burial mounds are therefore almost completely destroyed, but can still be recognised by their continued physical presence in landscape.	
NAME	**Alzenau**
Description	Burial mounds; two clusters
Temporal or cultural frame	Unknown prehistory
Ground truth estimate	20
Nearest administrative UID	194524; 196034
File number	D-6-5920-0007; D-6-5920-0021
Sub district	994;2291
The two clusters of burial mounds at Alzenau are situated in an area of former migrating sand dunes, now held down by forest and canopies. However, this highly complicates the identification of burial mounds in the area. Undoubtedly there are two clusters of burial mounds in the area, but to determine their extent is extremely difficult by remote investigation, as well as by field investigation. Therefore the finale estimate is a very rough estimate, and the southern cluster, C2, seems to be the most prominent of the two.	

A more comprehensive representation of the nine individual sites can be seen in appendix 3A and 3B. For the applied means of automatic information extraction from LIDAR data, a range of ground truths are therefore established. The detection of archaeological monuments within digital landscapes of LIDAR data is a discussion of positive and false positive detection by confidence improvement through shapes and patterns. To define limits of shape and patterns of cultural heritage, it is necessary to determine a baseline of impact. A baseline of impact will be determined by simple shape detection of burial mounds in the digital landscape. This includes a discussion on how to describe and interpret natural mounds from cultural mounds, and how to classify the range of artificial mounds in the landscape from a wide array of cultural and natural impacts on terrain and surface. Because, terrain is dynamic through time and space by living and natural manipulation of soil composition and decomposition, and thus patterns of the past and present are mingled together as details in the landscape. Detection and comparison by automated and manual means, will be continued and applied in chapter 5, but it is necessary to establish some fundamentals before. Because, the ground truth estimate are verified burial mounds. However, all false positives can potentially be true burial mounds, and only truly rejected or confirmed by the archaeological practice. The visual and remote distinction of artificial cultural mounds and natural peaks, are even further complicated by the wide array of artificial mounds constructed and amassed in different contexts, and different periods of time. Therefore, a remotely detected false positive, is almost never a complete rejection or verification of origin and purpose. Because, even though a burial mound has a simple shape and outline, simple shapes and outlines similar to burial mounds are also constantly constructed and shaped by other means of cultural and natural manipulation of landscape. This naturally, is the implication for all geometry in landscape. It is constantly produced, reproduced and fragmented by wear and tear through time. Linear features are also a simple shape, and can be found in even greater abundance in the landscape, but linear features in the landscape are often more connected to more recent history, i.e. roads, ditches and dikes (see Vletter 2014) . Even more so, linear features such as roads, ditches, and dikes, are often reused as similar details in landscape with slight alterations, making it near impossible to determine origin and authenticity. More complex shapes of monuments in the landscape, on the other hand, might have more unique features possible to detect, but is impacted by the equally unique record of fragmentation. Very unique structures has very unique situations of decay and deconstruction, making it almost impossible to define variable standards. If the variable definitions for complex features are simplified, the result will be a wide array of similarities detected in the landscape by modern and natural origin. Consequently, even though burial mounds have many similar false positive burial mounds in the landscape, the same can be said about most monuments in the landscape. All features change curvature, outline and shape according to wear and tear, smoothing unique details to a degree where it becomes the slight curvature changes in landscape that is the only possible thing left to detect. With a reasonable result on detecting mounds, the mound variables are as a result possible to be extended towards locating the fragmented and deconstructed records of the past, because within lies many unique shapes. The burial mound in it itself might therefore not be simple, but the mound is simply the ever present shape of any given landscape. The detection of a mound, compared to detection of a burial mound, can subsequently be based on the detection of macro patterns, rather than micro patterns. Thus, the spatial and contextual relationship can be more important than individual outline of natural and cultural curvature in landscape.

3.3 ARTIFICAL MOUNDS

Artificial mounds are an ever present landscape detail across the known inhabited world as constructs from both the past and the present. The construction of artificial mounds are a narrative of construction and reproduction of socio-cultural symbolic guidelines, but also a narrative of practical principles and natural composition and decomposition of soil and materials to adapt to environmental variables in time and space. All artificial mounds are the composition and decomposition of earth and stones intentionally accumulated, but also depicting the gradual scatter of soil and materials through time. Artificial mounds are structured or accumulated entities meant to serve a practical purpose, a symbolic purpose, and/or both at the same time. A practical purpose is as a byproduct of other activities, such as construction or material displacement. Artificial mounds can also aid by its spatial characteristics as a structure offering an advantage compared to the natural landscape, e.g. visual or defensive improvement. Meaning, artificial mounds can be constructed for both the living and the dead. They can be constructs of intentionality and unintentionality and as markers of the once lived landscape, re-used for the living. All mounds have extents gradually scattered in space through time. However, both natural and cultural mounds can equally be accumulating soil, sediments, and materials by decomposition. Therefore, a distinction between artificial and natural mounds can be difficult, if not impossible without excavation and cross-sections revealing horizons. The alternative is looking at macro patterns in order to determine structure and variables for composition and decomposition of soil, sediments, and materials in the landscape. The landscape pattern indicates origin of both natural and cultural construction by soil horizon stratigraphy, but traces of movement and erosion in terrain can equally reveal natural and cultural impact on the landscape. For this purpose, LIDAR data is well suited for visualizing terrain composition and decomposition from a macro scale perspective. The landscape footprint by the lower part of the mound is commonly rounded gradually outward from the summit. Artificial mound variations exist, with for instance burial mounds also supplementing with other architectural features such as stone settings, ditches, walls, and chambers inside. Equally, for burial mounds variations exist over deposition in or out of the summit, and as cremations and inhumation deposits with or without chambers in a wide variety of shapes. Therefore, physical mound footprint in landscape changes in correlation to structural details and deposition in relation to a summit. Common for all artificial, as well as natural mounds, is, that the modern shape of curvature and peak are simplistic due to temporal and spatial wear and tear by external impact through decomposition of soil and materials by living things and weather. Thus, the physical composition can be naively defined as rounded geometries in landscape shaped by environment and time. Thus, classification between natural and cultural mounds is difficult, but even more so between artificial mounds created for practical purpose, or artificial mounds created for symbolic purposes (FIGURE 23 & FIGURE 24).

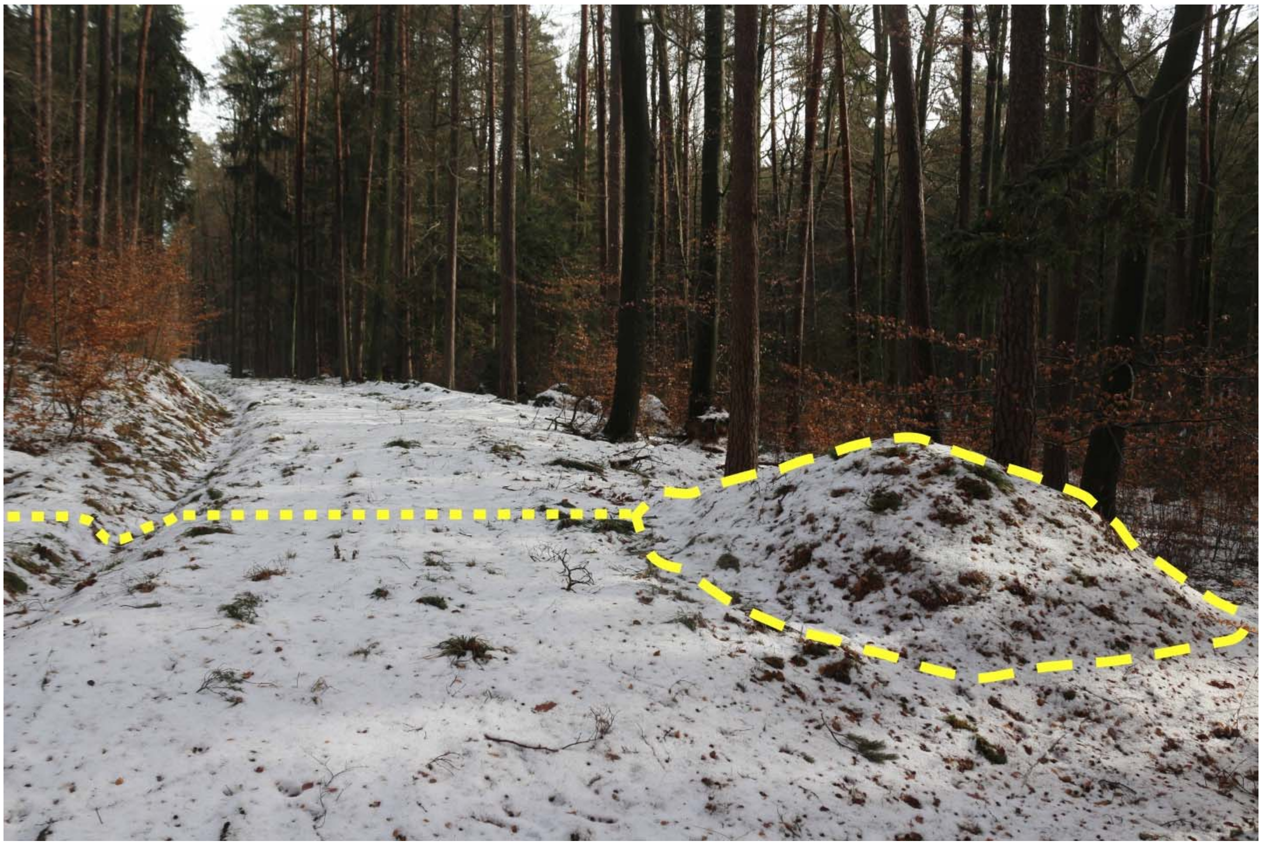

FIGURE 23: ARTIFICIAL MOUND CREATED FOR PRACTICAL PURPOSE. A STANDARD ACCUMULATED MODERN PEAK OF SOIL AND MATERIALS LOCATED NEXT TO A ROAD AND DITCH IN THE FOREST NEAR MAROLDSWEISACH, UNTER FRANKEN. VIEW TOWARDS EAST.

The result is confidence value of automation requiring validation and verification by other criteria than outline detection. Segmentation is a valid means of improving our ability to process digital landscapes, but classification is restricted to other standards of analysis unlikely to remove the human interpreter. Consequently, changes of pattern perception from micro to macro patterns and perspectives are necessary to describe landscape details by efficient and quantifiable information extraction. However, learning and reading a landscape towards known target specific details is easier for both a human and computational interpreter, compared to a broad application to make sense of all unknown details in the cultural landscape. Equally, we can segment all mounds in the landscape, but remote classification will continue to be a matter of settling on certainty and confidence values needed for both a human and computational perspective. To initiate, it is necessary to settle on how to understand the overarching concept of a burial mound, and the simple artificial shape behind it.

FIGURE 24: ARTIFICIAL MOUND CREATED FOR SYMBOLIC PURPOSE. COMMON WORN AND ROUNDED OUTLINE OF A BURIAL MOUND. ABOVE: LANDSCAPE WITH BURIAL MOUND. BELOW: DRAWN BURIAL MOUND OUTLINE. BM110. IN THE FOREST NEAR MAROLDSWEISACH, UNTER FRANKEN. VIEW TOWARDS EAST.

Cultural burial mounds are barrows, tumuli, graves, kurgans, cairns, passage graves, mortuary enclosures, earthen-work, earthen-covered artificial curvature, and many more. More overarching or describing terms and names exist, but similar to all burial mounds is the construction and accumulation of earth, timber, stones or other materials covering a grave, commemorative, or several graves by past cultural manifestation (Bradley 1998; Scarre 2002). Simply stated, burial mounds are constructed and accumulated cover over or for the dead ancestors, but the term burial mound does not cover the internal architecture by cultural strategy of deposition of the dead. Thus, a burial mound is the overlapping term used for a wide variety of cultural practice as a structure in the landscape by representation. Because, the burial mound is created in composition and resonance with the cultural and spatial context to mimic, reference or reproduce socio-cultural guidelines (Scarre 2002; Tilley 1994; 1996). The symbolic purpose of burial mounds are of a tangible visual representation and significance by landscape alterations from a culture specific outline (Bradley 1993, 95-103; 1998, 10; Renfrew 1973; 1983; Scarre 2002) to establish, negotiate, and maintain social relationships (Goldhahn 2008; Holst & Rasmussen 2012) but equally as artificializing and manipulating nature (Midgley 2013; Tilley 1994; 1996), and as claiming community establishment and ownership (Hodder 1984; Renfrew 1981; Sherratt 1990). Thus, there is no single purpose for burial mounds in the landscape, but rather as an entity to a variation of practical and symbolic meaning for the living and the dead. However, it is a term integrating the cataloguing of a past or present day earthen cover, shaping the landscape over the dead as a risen elevation, mound, and monument in contrast to the natural curvature of landscape (see FIGURE 24). Each artificial mound entity utilizes individual components of accumulated materials, but with regional factors by source material availability. Thus pragmatic principles are also evident for the identity of the burial mound. The visible remains of the artificial mounds are laterally and vertically modified by a range of cultural and natural factors impacting the physical extent, and the life cycle of a burial mound is therefore not only understood by its point of origin, but rather by its adaptation and modification through time. The burial mound nevertheless, is defined as a singular entity collectively impacted in state of preservation and conservation by changes to physical extent in context. The physical state of a burial mound is an enclosed entity sealed by internal environment, creating individual stable ecosystem, and thus different degrees of preservation and conservation of organic and inorganic materials. The physical state of burial mounds vary from dry and aerobic almost deplete of organic materials, to wet and anaerobic with complete organic preservation. Dependent on internal sealed environment, the pH levels within burial mounds ranges from slightly alkaline to acidic with pH levels below 3. Maintaining the physical outline and extent implies preservation of water-saturation and iron pan (Breuning-Madsen & Holst 1998), and thus defines the state of preservation. The environment is constructed from last penetration of iron cap and outline from external natural or cultural impact. The amount and quality of information within the burial mound is therefore not directly correlated to the mere physical presence or absence in relation to original mound (Holst et al. 2006). As a result, preservation of metal and organic material varies greatly in different environments. Thus, the necessary active preservation of burial mounds is a correlation to preserve a stable and continued internal environment. Modifying the landscape and altering moisture levels, such as by drainage or water displacement, changes the previous chemical balance and environment around, and thus affects accumulated conservation within the mound. The amount and quantity of information preserved from barrow to barrow, changes in relation to the landscape, and thus impacts the necessary active preservation precautions to maintain the accumulated passive conservation within the sealed ecosystems. These are very important factors to consider for non-destructive preservation of cultural heritage, and especially burial mounds in the landscape. Because, the burial mounds are not just important as monuments in the landscape, but also as entities preserving information near the time of origin construction. However, the dangers of destruction for burial mounds are many, and naturally the physical changes to the outline of the monuments have the most impact on preservation of information. Burial mounds in the landscape are in danger of being destroyed despite general protection by rules of preservation from modern construction, forestry, and agriculture (Asingh 2001; Jørgensen 2001). The impact of environment, but also negligence or intentional destruction, randomly changes and destroys monuments in the landscape. But even without random occurrence of external impacts, it is estimated that cultivation alone causes continued erosion by 1 cm/year on non-scheduled burial mounds in the landscape (Holst et al. 2006, 68-9). Records of ground truth are therefore an absolute necessity for monitoring changes in landscape. Automated detection and automated *change detection* are subsequently necessary steps of modern cultural heritage management in order to preserve both the physical and digital record of our landscape by being able detect change, and repeatedly calculating modern impact in the continuous flow of new datasets.

3.4 CHANGING LANDSCAPES IN LOWER FRANCONIA

Landscapes are ever changing by construction and deconstruction. No terrain remains stable, and all recording and documentation are static representation and visualization of given space in given time. Remote investigations are therefore constructed representations of given space in given time. Landscape is inevitably changed and changing in area of interest since origin of construction, but also since point of recording and documentation. As a result, digital truths of elevation models are not always similar to ground truths. From Lower Franconia, this is exemplified from predicted digital truths by remote visual LIDAR detection of burial mounds at the nine areas of interest introduced above. The nine sites are field surveyed to compare digital truths and ground truths to create a record of burial mounds within the landscape of the areas of interest. This is presented in appendix 3B. However, in the appendix 3B is only represented the actual burial mounds within the landscape, and not the details changing landscapes, and misconceptions between digital and analog information. Because, as was already revealed in chapter 2,6, desk based investigations and field surveys do not exclude one another, but rather compliments each other by revealing hidden details not completely discovered by one approach alone. Similar for the nine areas of interest, not all details revealed by LIDAR are true, but the LIDAR data also revealed much information not possible to attain from field surveys alone. Some burial mounds were not detected by visual detection, some changed classification when closer inspection was carried out by the field survey, and some details was no longer part of the landscape since the original LIDAR recording and present day representation of landscape. Digital artefacts, meaning remnant and patterns created by the remote recording, are an ever present problem, but in one instance included the disappearance of a burial mound likely destroyed by modern forestry (FIGURE 25).

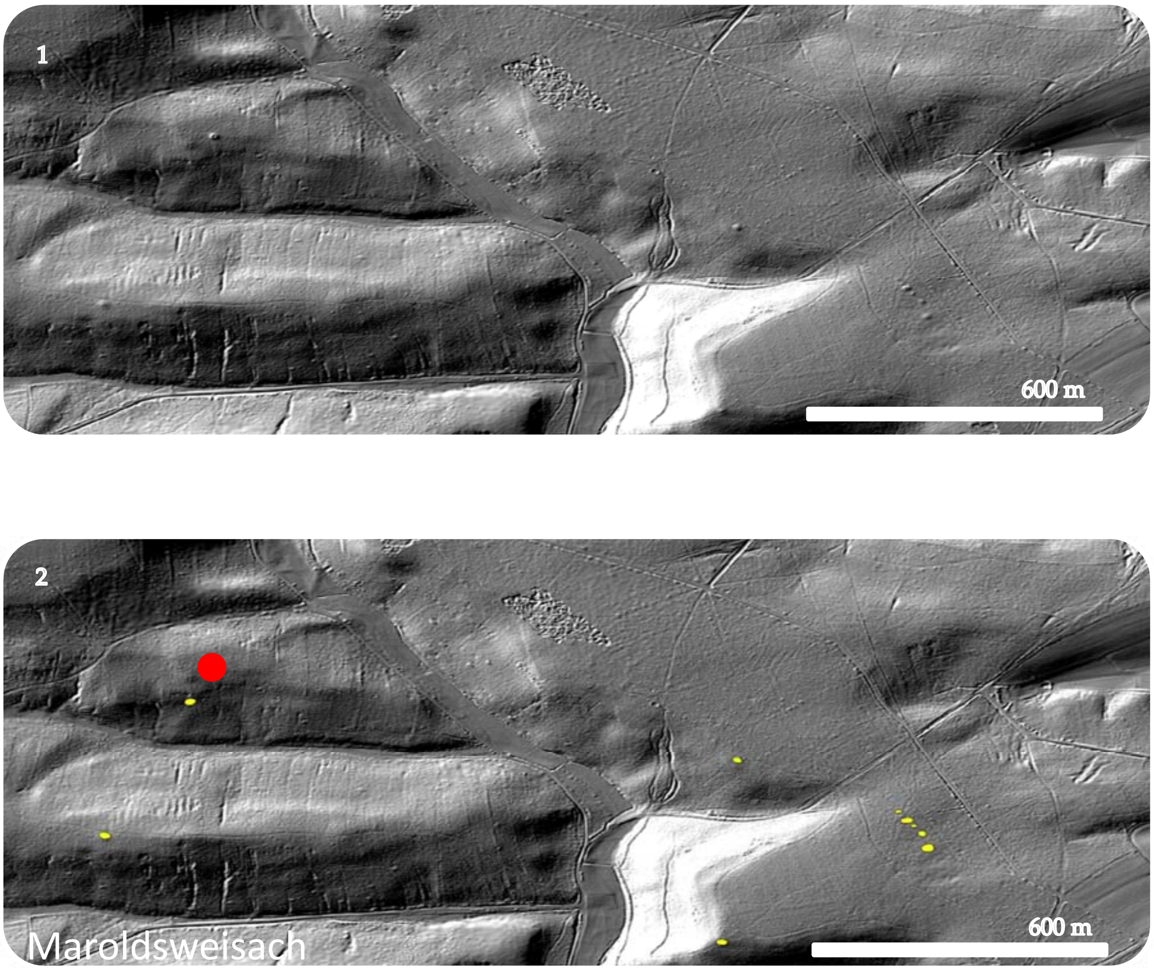

FIGURE 25: MAROLDSWEISACH DTM WITH INDICATION OF DETECTED BURIAL MOUNDS. RED CIRCLE INDICATES THE MISSING VISUALLY DETECTED BURIAL MOUND, BUT NOT POSSIBLE TO RELOCATE BY FIELD SURVEY. SHADED RELIEF: AZI. 45°, 270 ANGLE.

The visually detected burial mound indicated in raster 2, FIGURE 25, was not possible to relocate by field survey, despite the area containing a distinct looted burial mound within the DTM. Just below the missing burial mound, a new burial mound was located by field survey that was not possible to remotely detect from desk based investigation by the DTM (FIGURE 26; FIGURE 27).

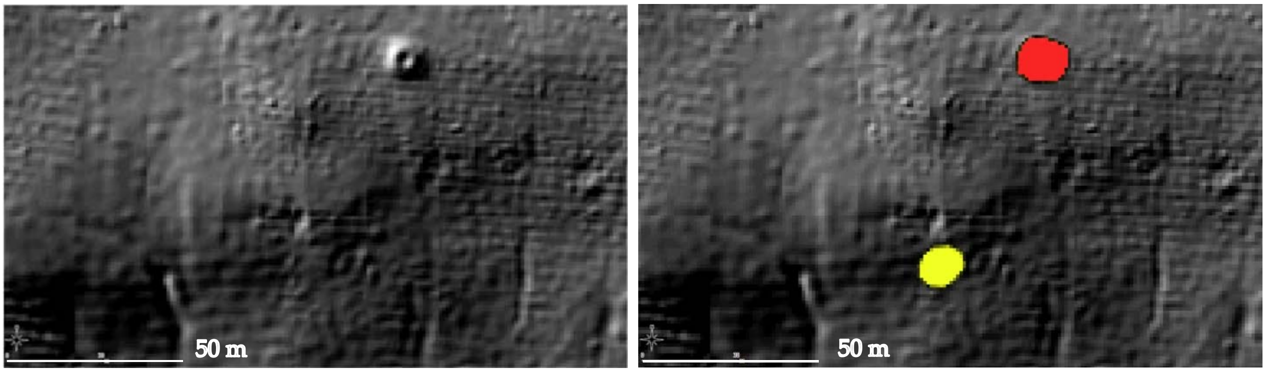

FIGURE 26: LEFT: DTM WITHOUT INDICATION OF BURIAL MOUNDS. RIGHT: INDICATION OF TWO BURIAL MOUNDS. RED: MISSING, YELLOW: FIELD SURVEY DETECTED. SHADED RELIEF: AZI. 45°, 270 ANGLE.

FIGURE 27: LEFT: AREA OF MISSING BM IN MAROLDSWEISACH. RIGHT: FIELD SURVEY LOCATED A SLIGHT ELEVATIONAL CHANGE NOT VISIBLE WITHIN THE DTM. 20 CM ELEVATIONAL VARIATION IN THE LANDSCAPE INDICATED A LIKELY BM BY A DISTINCT CIRUCLAR STRUCTURE.

Artificial mounds in the landscape can be constructions of any given time, but reveals indirect information by macro patterns in landscape and contextualization to other known details. For the area of Maroldsweisach, the situation is similar. It is not necessarily the micro patterns of elevational change and artificial mound placement that determines classification, but rather the macro pattern of context. Two clusters of burial mounds are located within the area investigated and shown in FIGURE 25, but they are heavily altered from original representation, with most likely destroyed and removed mounds in between. However, many details of the former burial mounds are still possible to locate within the landscape, if overall macro patterns are capable of indicating areas of interest. To further cultural heritage management and detection, the application of macro segmentation can therefore contribute meaningful patterns to understand landscape. Thus, it is a matter of segmenting landscape to a degree where individual details are not essential for primary detection and interpretation for areas of interest, such as complex grave field distribution. Accordingly, it is a matter of defining approaches to improve macro pattern detection substantial enough for micro patterns to be investigated. Simple shape detection allows for macro pattern extraction, but do not construct micro patterns of certainty regarding origin. To apply pattern recognition, the perspectives should therefore be focused on macro patterns rather than micro patterns in the landscape. To understand how to best apply, it is necessary to define present practice, and impact in the field of cultural heritage management and detection. This will be visualized and exemplified in the following chapter. The following chapter will define state of the art for automated detection, and best practice for segmentation and simple shape detection within remotely sensed data, and particular for LIDAR data. This will be done to make a quantifiable representation of the development of the field, meanwhile locating best approaches for improving quality of information extraction by notions of cost efficiency, and increased or improved use for the archaeological community. However, it is necessary to remember that remotely sensed information is not always the same as the perceived information gathered from the ground. Details and information changes, and landscape is constantly manipulated, altered, and shaped by external and internal factors.

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4. STATE OF AUTOMATED AND SEMI-AUTOMATED DETECTION WITHIN REMOTE SENSING ARCHAEOLOGY

The following approach focuses on automated procedures for the detection of monuments in the landscape as part of archaeological mapping. The approach is a reaction to understand automated detection across domains and academics fields, as well as a response to the increased availability of data from vast areas of diverse landscape shaped by the past and present. Especially with the availability of LIDAR data, digital landscape analysis and detection of cultural heritage monuments has developed rapidly during the last 15 years. Consequently, this increase in information has amplified the need for automated procedures for monitoring, surveying and detection of known and unknown monuments. Whenever tools and procedures, such as these, cross knowledge domains they invariably split existing disciplines into those familiar and engaging with the new, and those that do not. The pattern by which new knowledge is spreading, and where appropriation takes place, holds vital clues for understanding the long-term impact of the procedures in questions. To understand development of the field and best practice, automated procedures can also help to analyze the use of automated detection for cultural heritage studies. In this chapter, this will be done by a systematic literature review to get a simple perspective of publication intensity. In a second step, applied statistics of network analysis will be used to generate a dataset that contains information relevant for the dissemination of knowledge. The goal of this chapter is to see publications patterns in order to determine state of the art and best practice to be applied in the following chapter. The network analysis helps describe the paths taken by the community, and how this impacts the field today.

4.1 QUANTIFYING THE FIELD

The analysis of patterns within automated procedures for cultural heritage and monument detection has two components: First it is initiated by a Systematic Literature Review (SLR) to reveal overall trends. The overall trends are subsequently analyzed using Network Analysis (NA) to gain a more detailed view of community structure and knowledge brokerage. The SLR uses Systematic Search Queries (SSQ) of bibliographic databases and citation indexes. The NA is based on a sample dataset for referential connectivity. The NA citation data can be referenced by appendix 4A, 4B, and 4C. By looking at the historical development of the field through a quantitative lens, the hope is to reduce personal bias and let the data of publications and citations do the talking instead. The results of the analysis can assist planning for similar projects by pointing to the hidden or missing connections of clusters of research.

Quantitative approaches principally depend on the quality of their underlying datasets. The dependence on qualitative data for analysis is partly due to technical limitations in the citation databases. Without the ability to automatically generate larger randomized samples or to compare the topology of the graph with that of the complete corpus underlying the queries, it can only present an informed estimate of the real-world network. Just as these databases suffer from limitations in their collection process, e.g. collection based on English as lingua franca, they nevertheless provide a reasonably good estimate of different academic fields. Similarly, the core articles of the analysis present an estimate at the state of the field as it appears within these datasets. As time progresses, schematic models representing the field will equally develop. However, the following approach takes a dual approach to determine the field by the initial sample dataset for NA, as well as compare with an updated dataset by recommendations following a presentation given at the conference, Computer Applications and Quantitative Methods in Archaeology, spring 2016 in Oslo.

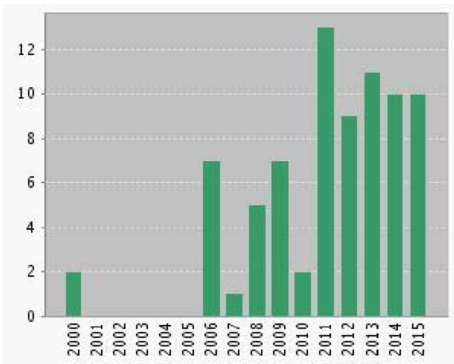
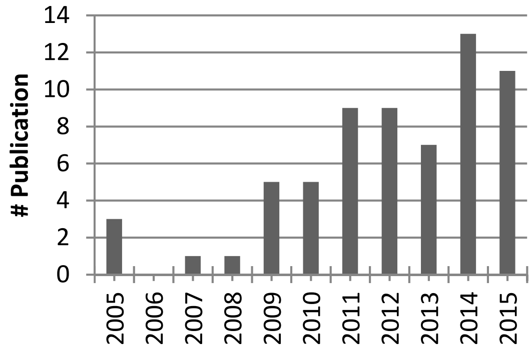
4.2 SYSTEMATIC LITERATURE REVIEW

Data for the SLR is collected from online publication indexes and SSQ. SLR produces a general overview for understanding the community and development of automated detection within archaeology. Web of Science, (WoS; www.webofknowledge.com) and Scopus (https://www.scopus.com/) were used as primary platforms for data extraction. Other potential databases for SSQ, are: Google Scholar, CINAHL, CAS Illumina Databases, EBSCOhost Databases, EMBASE, PubMed Central, Science Direct, and SciFinder Scholar. However, all the investigated online citation indexes provide a limited coverage of a field's literary corpus. Thus, data fragmentation remains a problem for automatic extraction of data via SSQ, because the corpus of articles lacks publications from lesser recognized journals and proceedings. Hence, qualitative selection of sample datasets enables a less impaired analysis in comparison to quantitative studies through online citation indexes. In its present state, online citation indexes are usually biased towards different journals in relation to access obtained, or in-house publication. Consequently, comparisons between the different citation indexes are not defined as 1:1. Patterns can still be compared, because they are indications of overall trends. But it is necessary that they incorporate a large source material for data to be comparable. WoS and Scopus are two of the biggest citation indexes at present, and both incorporate a large corpus of publications focused on remote sensing and cultural heritage, such as *Antiquity*, *Journal of Archaeological Science*, *International Society for Photogrammetry and Remote Sensing*, *Remote Sensing*, and many more. Figure 28 shows the results of the SSQ. The online journal and citation indexes indicate increasing relevance on the topic of remote sensing. By 2016 the data shows a reduced number of publications, but that is largely also a result of data extraction being performed mid-2016. All queries used combine two generic terms. More generic terms were experimentally queried, but few proved to show discernible patterns for dissemination of automated procedures in archaeological contexts. In addition to the selection bias favoring international peer-reviewed journals, a heterogeneous array of terms can designate automated procedures within archaeological practices[1]. All terms describe various advances towards automated and semi-automated means of segmenting and classifying remotely sensed data. The varied terms, however, make it difficult to locate specific tags that encompass all relevant data. Therefore, the SLR consists of generic terms to locate general tendencies and trends, such as: 'archaeology' (Ar), 'LIDAR (Li), 'remote sensing' (RS), and 'automatic detection' (AD). These terms contain the largest potential data corpus for a SLR, but cannot reveal a complete picture. Especially in the combination with terms such as 'archaeology' the tendencies are much more fragmented. One such example is the combination of generalized search terms of 'automatic', or 'detection' combined with 'archaeology', resulting in two hits. Consequently, the more generalized search term 'remote sensing' has been used to see the presence in search queries together with 'automatic detection'. The SLR reveals a prominent presence of remote sensing and LIDAR data within archaeology, but almost no relation to automated procedures. Within remote sensing the presence of LIDAR data grows exponentially. Equally, automated procedures grow parallel to remote sensing and LIDAR data within the online citation index of WoS, while Scopus indicates a more blurred pattern. However, none of the online citation indexes can indicate trends in the field of automated procedures for monument detection within archaeology. While other studies such as Tomljenovic et al. (2015) and Agapiou & Lysandrou (2015) effectively use SLR to enhance our understanding of remote sensing and automated procedures, this investigation uses NA, to complement the SLR. NA reveals the community of automated procedures within archaeology, which is otherwise not registered by the SLR. Thus, where the SLR fails, the NA can elaborate and highlight more present, different, and miniscule communities and trends. This gives the possibility to quantifiably review evolution of best practice for automated practice, and its pattern of application within archaeology.

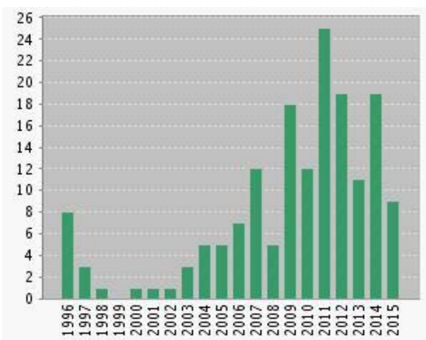
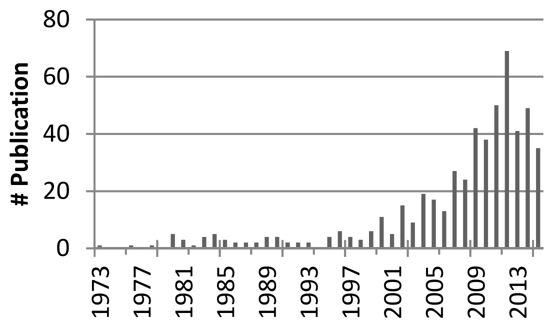
[1] The terms and keywords for the procedures are described by 'algorithmic procedures' and 'general methods'. Generic terms are given as: 'hough', 'canny', 'edge', 'line', 'shape', 'matching', 'extraction', 'detection', 'transform', 'object', 'template', 'attribute', 'texture', 'contrast', 'morphology', 'per-pixel', 'segmentation', 'classification', 'ontology', 'pattern', 'recognition', 'image analysis', 'automatic', 'semi-automatic', 'deep', 'machine learning', 'computation', and 'algorithm'.

WOS **SCOPUS**

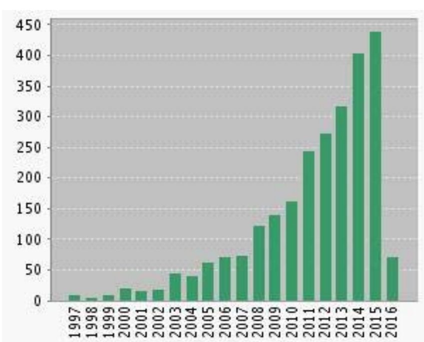
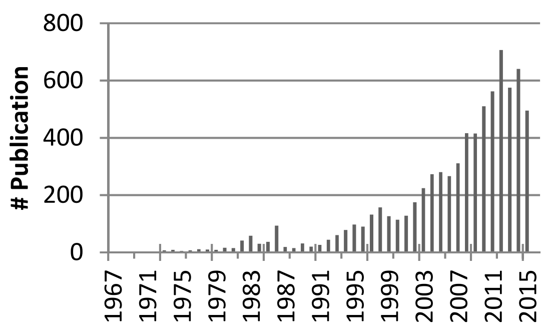
A: (Li) & (Ar)

B: (RS) & (Ar)

C: (RS) & (Li)

D: (RS) & (AD)

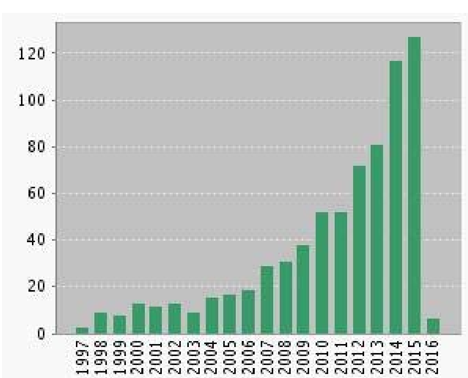
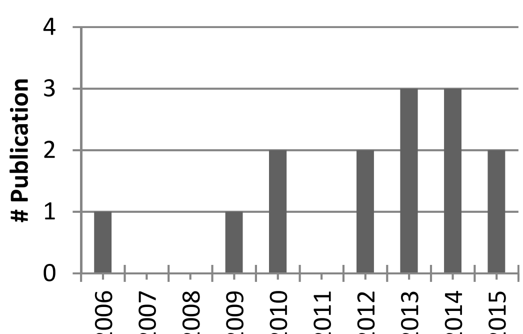



FIGURE 28: SCOPUS AND WEB OF SCIENCE (WOS) CITATION INDEX FOR PUBLICATIONS COMBINING:' LIDAR' (LI), 'ARCHAEOLOGY' (AR), 'REMOTE SENSING' (RS), AND 'AUTOMATIC DETECTION' (AD). THE Y-AXIS INDICATES PUBLICATION AMOUNT, WHEREAS THE X-AXIS INDICATES YEAR OF PUBLICATION

The timespan is defined by the possible extraction from the search queries of WoS and Scopus. Figure 9A illustrates the impact of 'LIDAR' data within 'archaeology'. Figure 9B illustrates impact of 'remote sensing' and 'archaeology', where usage history is extended back in time with increasing presence towards today. For 'remote sensing' and 'LIDAR', in figure 9C, a clear trend can be seen for the presence of LIDAR data within remote sensing studies with high increasing presence and impact. Lastly, figure9D illustrates the tendencies for the search terms of 'automatic detection' within 'remote sensing' as well as 'archaeology' to show the difference in impact within these fields. It also illustrates problems for understanding automatic procedures within archaeology. Within remote sensing and automated detection, the field is exponentially growing, whereas within archaeology the picture is more blurred with few articles recognized by the online citation indexes. Some included articles are not even relevant, but as can be seen in the reference list from the sample NA dataset (see appendix 4C) many more articles of interest exist. But even though the SLR does not provide a complete picture, it still gives solid indications as to the larger trends in-between different fields.

4.3 NETWORK ANALYSIS

To gain a more fine-grained understanding of the regional and intellectual shape of the community revealed by the SLR, this study turn to the advantages of network analysis. By generating a citation network based on a new qualitative sample dataset of 37 peer-reviewed core articles, the connections between individual publications and their authors, as well as the larger connected clusters that they form, can be traced and visualized. The modelled overall shape of the citation graph allows for a tentative assessment of the connectedness of the field as a whole, and visualizes its development and evolution. The initial 37 core articles all apply automatic detection by either a data or model driven approach. To minimize referential bias, the dataset is restricted towards one article per main author, and exclude articles with high degrees of overlap between authors and co-authors between separate publications. The publications in the NA sample do not represent all publications related to automated procedures for monument detection, but rather a diverse sample to probe the structure of connections between different aspects of the field. The modelled citation will later be validated by adding additional articles to the dataset, to see if the patterns change. The initial citation network consists of 1075 publication nodes and 1160 directed citation edges. It includes a variety of authors, and models the evolution of the field between 1999 and spring 2016. As a result, the connectivity of the graph puts further emphasis on intellectual brokerage between loosely connected components at the exclusion of self-references and repeated (re-)publications by identical groups.

The mean cooperation between authors is 1.105 per article. Within this selection (see Figure 29) 20 articles focus on aerial imagery from satellites and airplanes, 17 articles focus on LIDAR data. 21 articles concern technical questions, and 16 concern cultural heritage questions. 32 articles focus on data driven and attribute analysis, whereas five articles specifically concern “model driven” and “template matching”.

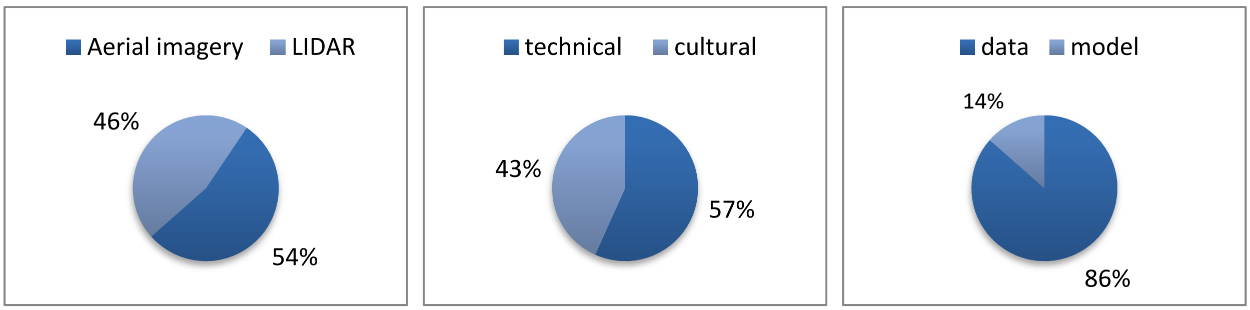


FIGURE 29: FOCUS WITHIN THE QUALITATIVE SAMPLE DATASET OF 37 PUBLICATIONS FOR THE NA

Only a few articles include institutional affiliations of their authors at the time of publication, so information was manually supplied for the 37 core publications by first author. In Figure 30 it can be seen that the field has global reach, but with a rather Eurocentric focus. This is likely also a result of personal institutional or linguistic bias, and of snowball sampling. A similar regional focus occurs with respect to places of publication from the bibliographical metadata. Yet, in today's publishing environment this has limited analytical potential, given the prevalence of English as scientific lingua franca and academic publishing practices.

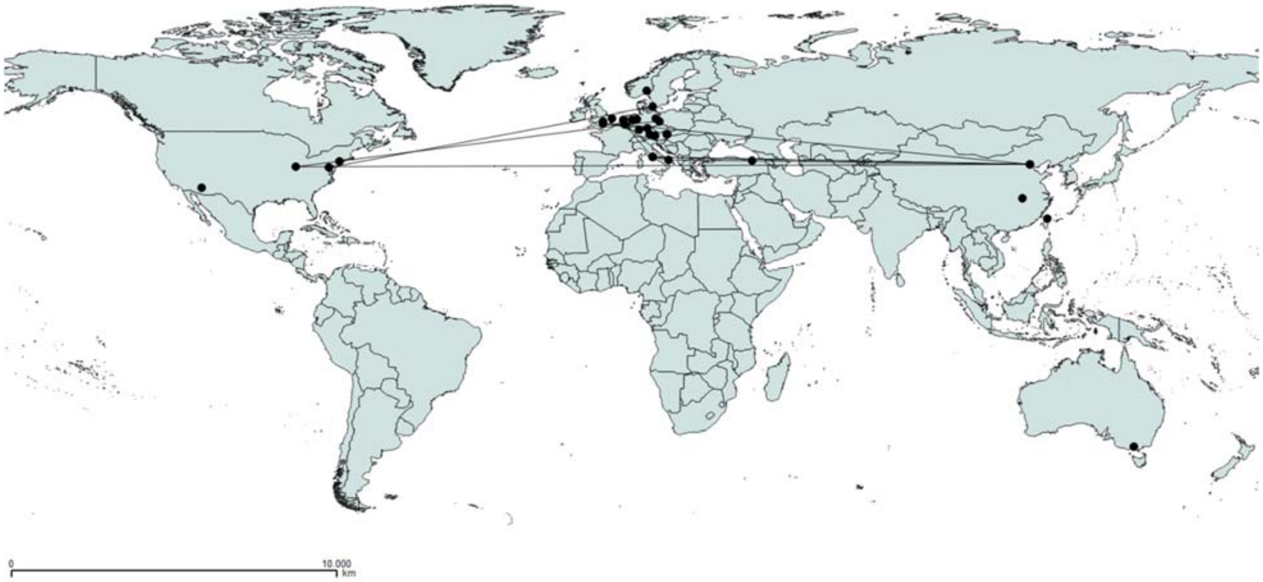


FIGURE 30: INSTITUTIONAL AFFILIATIONS OF THE NA DATASET FROM 37 PUBLICATIONS BY FIRST AUTHOR

Institutional connection by reference indicates connection by direct or indirect influence. To review the pattern of institutional affiliation, Figure 31 indicates modularity in three distinct groups by color range. The three distinct modularity groups are connected by similarity of references, but also indicate collaboration or influence. Despite the Eurocentric focus of the dataset, Figure 31 also gives indications as to directions of international collaboration. The 1st modularity group is highly internationally connected; whereas the 2nd modularity group has a very central European connection. The 3rd group equally has an international connectivity, but with a somewhat North American focus.

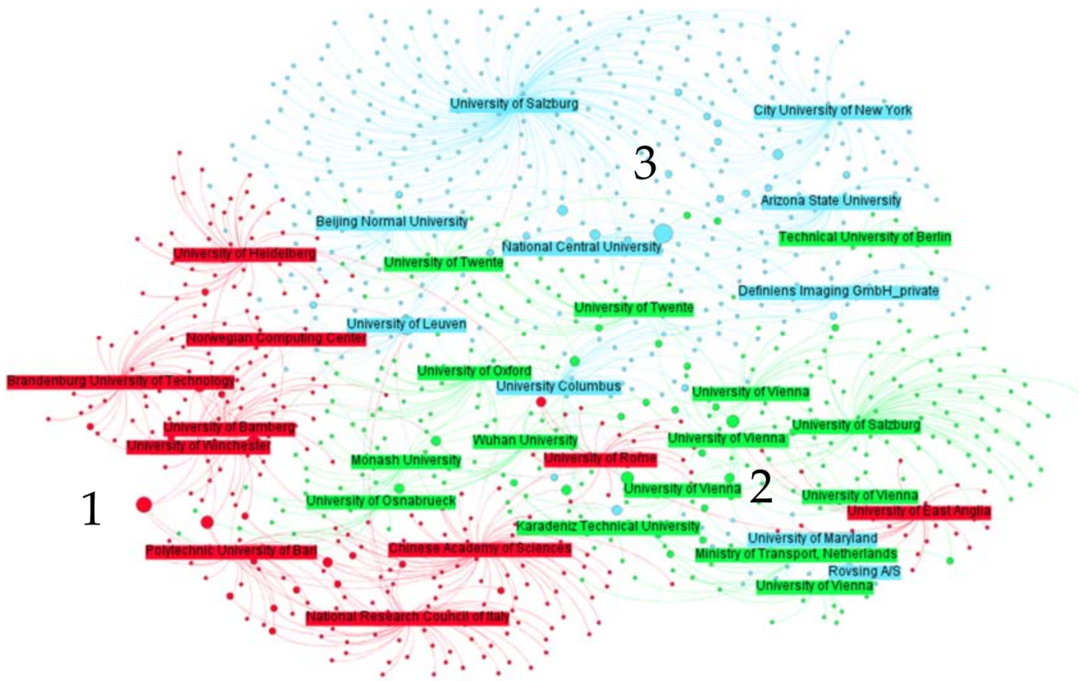


FIGURE 31: INSTITUTIONAL AFFILIATION BY MODULARITY IN 3 GROUPS: 1. DARK RED, 2. LIGHT GREEN, 3. LIGHT BLUE

The construction of three distinct modularity groups is also a result of field of field focus on either primarily technical or cultural questions for research topic (Figure 32).

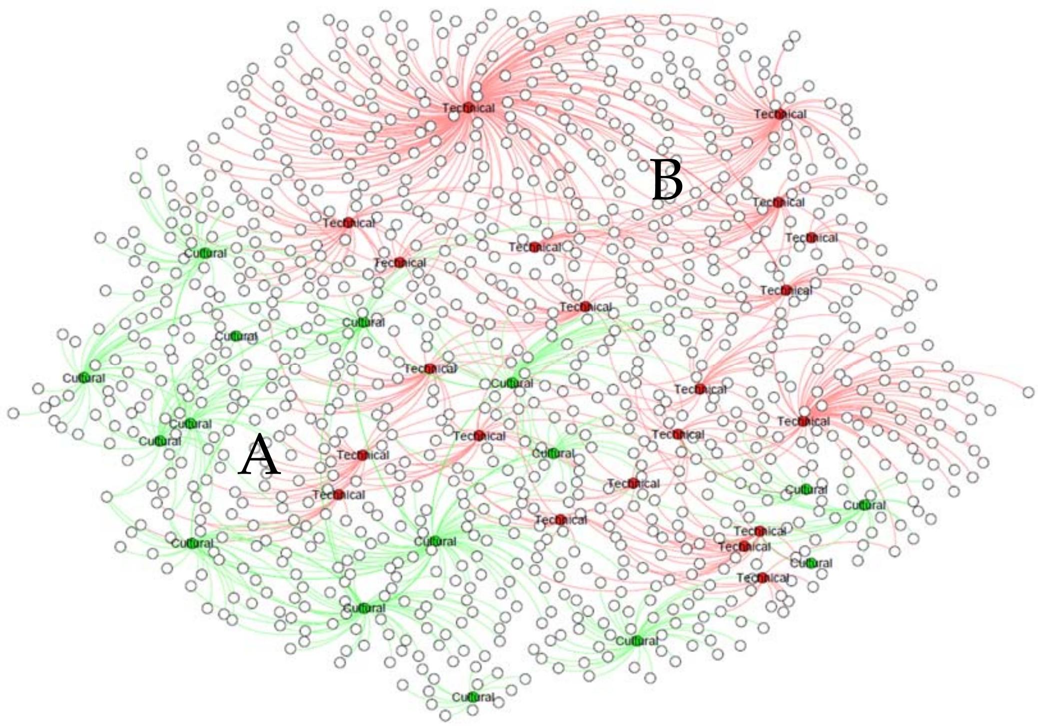


FIGURE 32: PRIMARY RESEARCH FOCUS: A. LIGHT GREEN, B. RED

By comparison of Figure 31 and Figure 32, it can be seen how the modularity group 1 is aligned with articles focused on automated feature detection for cultural heritage and archaeology, whereas modularity group 3 is focused on automated feature detection from a technical point of view towards a wider array of fields. The modularity group 3 is to a large degree focused on building footprints towards a contemporary classification of landscape, where modularity group 1 is focused on the ancient landscape. This modularity separation is natural given the input dataset of 43 % of primary articles focused on cultural aspects of automated detection and classification, and 57% of the primary articles focused on technical or more contemporary aspects of automated detection and classification. However, modularity group 2 in Figure 31, becomes something different. Modularity group 2 is the mediator between the other two modularity groups. Thus implying a wider depth of institutional affiliation towards a bigger field, and thus perhaps the most influential group by having and in- and out-degree of connectivity to the whole field of automated detection within remote sensing. This connectivity is determined by cross-references, meaning it is important to determine the sources of co-citation in order to understand the differences of perspectives. The citation network shown in Figure 33, uses Force-Atlas layout. This citation graph forms the basis for applying community detection algorithms, analysis of subgraphs, and event type information. The relative position of nodes remains consistent from Figure 33 to Figure 36 below. Figure 33 shows the full scope of the citation network. When viewing the full citation network, the patterns become illusive by the amount of information present. It is therefore necessary to filter to reveal patterns of interest for the field of automatic detection.

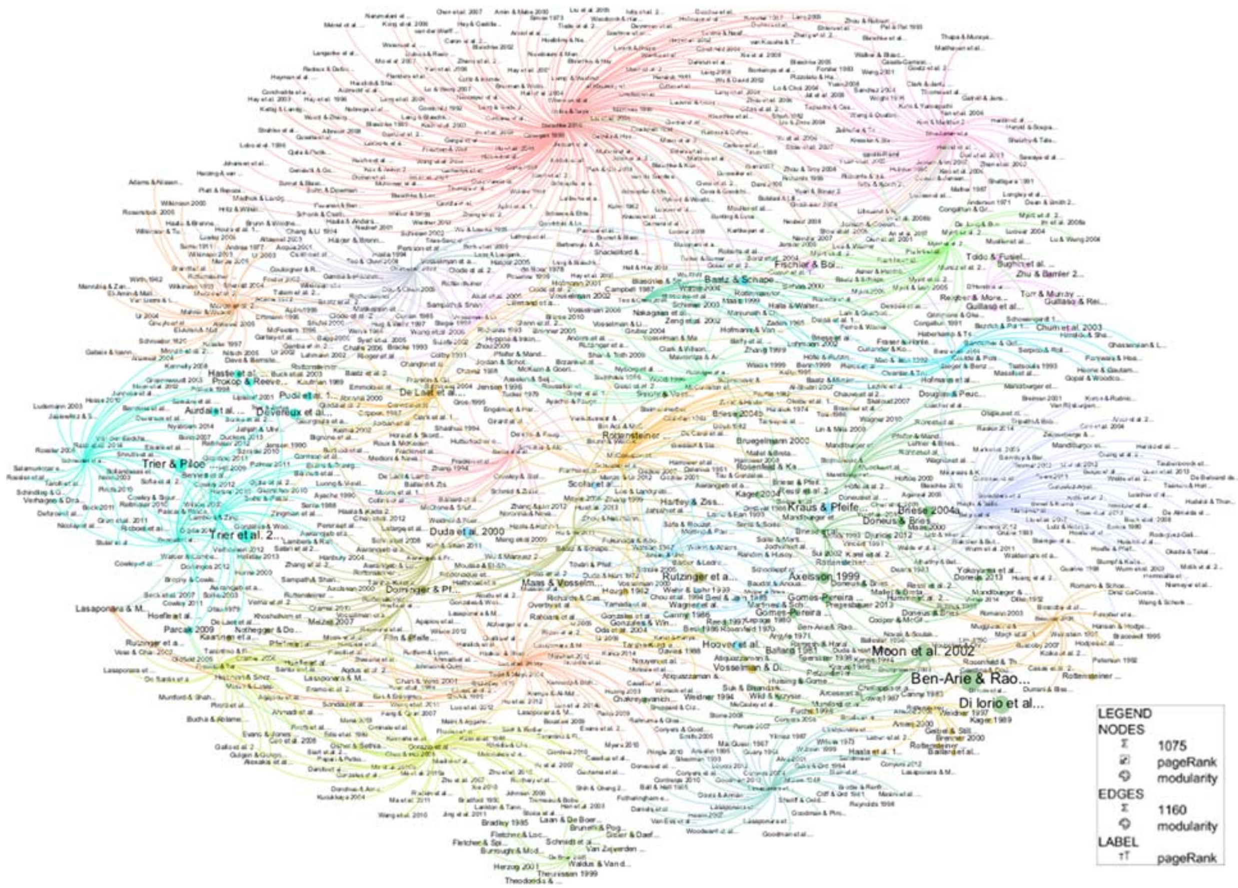


FIGURE 33: THE FULL CITATION NETWORK

In Figure 34, PageRank (Page et al. 1999) determines both node and label size. By itself, it is a good indicator of measuring academic impact. In the following figures, PageRank is contrasted by centrality to assess the academic impact of individual publications (see also Yan and Ding 2011). The prevalence of egocentric clusters such as the 190 mostly isotopic nodes related to the article of Blaschke 2010, results in a sparse graph with a density of 0.001 and 4 main components. By filtering nodes with a degree > 1, Figure 34 allows for a clearer view of those publications forming the well-connected core of the network (10.7% of nodes). The differences in node and label sizes are striking. These differences indicate competing ways in which publications are significant for the field. Blaschke 2010 draws upon the most citations, but only a small part is in turn connected to the core group. Ben-Arie and Rao 1993, on the other hand, occupies a central role for authors who in turn inspire other authors within the discipline. This becomes even more evident when comparing the subgraphs for in- and out-citations in Figure 35 and Figure 36. To derive these subgraphs, nodes are ignored which have zero in- or out-degree respectively, which as a consequence filter isolated nodes from the remaining set.

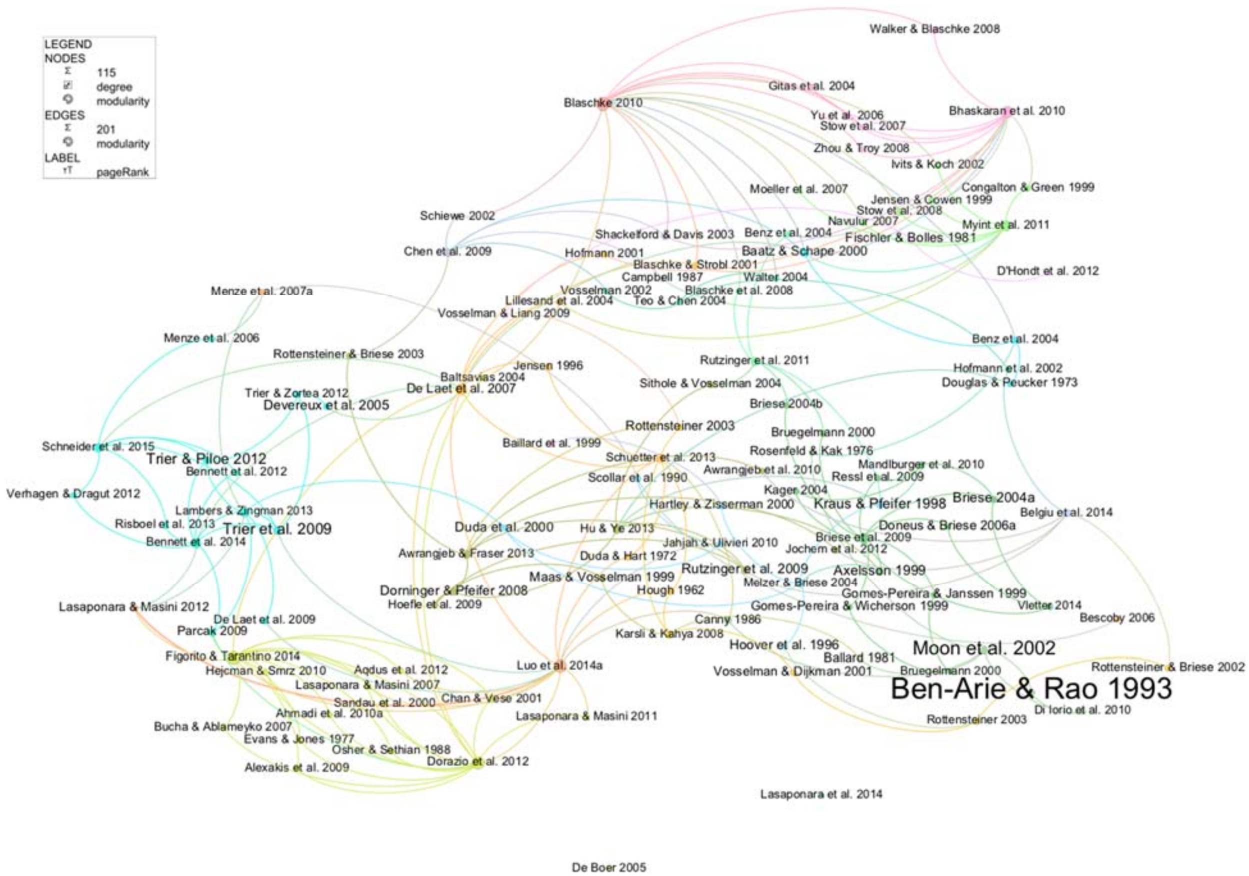
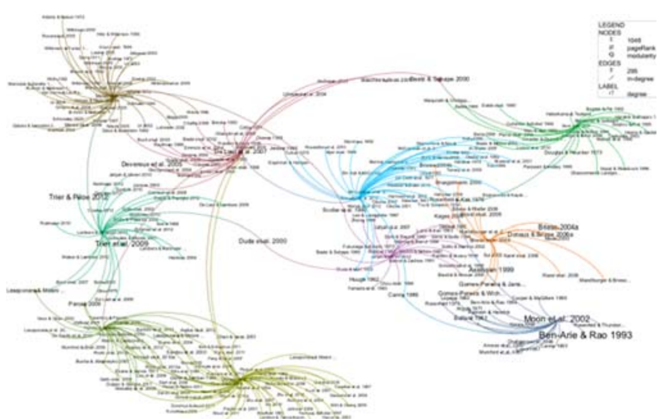


FIGURE 34 SUBGRAPH CORE CITATION NETWORK WITH DEGREE > 1



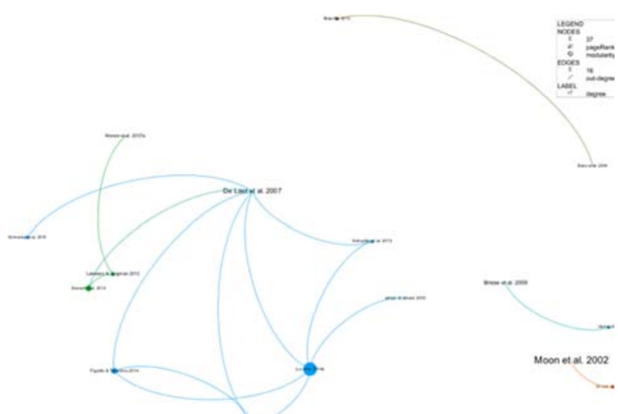


FIGURE 35 SUBGRAPH IN-CITATION

FIGURE 36 SUBGRAPH OUT-CITATION

In both cases Moon et al. 2002 and Ben-Arie and Rao 1993 play a significant role, albeit as part of small out-citation components. De Laet et al. 2007 and Luo et al. 2014a show the most consistent impact across all measures, along with others such as Dorazio et al. 2012 who rank in the top ten across different measures (see Table 9). This sequence of sub-graphs explains the discrepancy in impact that different means of measurement capture in the original citation network, displayed here by modifying nodes and label size independent of each other.

TABLE 9: COMPARISON OF TOP 10 CENTRALITY MEASURES (MULTIPLE APPEARANCES IN BOLD)

RANK	**PUBLICATION**					
	BETWEENNESS		PAGERANK (0.00…)		DEGREE	
1	DE LAET ET AL. 2007	154.5	BEN-ARIE & RAO 1993	…2129	BLASCHKE 2010	191.0
2	***DORAZIO ET AL. 2012***	87.5	***MOON ET AL. 2002***	…1582	BELGIU ET AL. 2014	69.0
3	***MENZE ET AL. 2007A***	82.0	DI IORIO ET AL. 2008	…1582	LUO ET AL. 2014A	66.0
4	LAMBERS & ZINGMAN 2013	65.0	TRIER ET AL. 2009	…1008	BHASKARAN ET AL. 2010	62.0
5	*SCHUETTER ET AL. 2013*	32.5	TRIER & PILOE 2012	…0890	***DORAZIO ET AL. 2012***	53.0
6	BENZ ET AL. 2004	24.0	KRAUS & PFEIFER 1998	…0691	LASAPONARA ET AL. 2014	44.0
7	JAHJAH & ULIVIERI 2010	21.0	AXELSSON 1999	…0604	***MENZE ET AL. 2007A***	41.0
8	FIGORITO & TARANTINO 2014	20.5	BRIESE 2004A	…0558	MYINT ET AL. 2011	39.0
9	***MOON ET AL. 2002***	17.0	RUTZINGER ET AL. 2009	…0494	*SCHUETTER ET AL. 2013*	37.0
10	BRIESE ET AL. 2009	14.0	DEVEREUX ET AL. 2005	…0456	CHEN ET AL. 2009	37.0

Looking at the evolution of the network over time in Figure 37 it can be seen that a shared body of references is only slowly coming into being. While the articles in the dataset were published between 1999 and 2015, their references go as far back as 1820 with the majority of publications (43%) falling between 2011 and 2015 as can be seen in the long-tail plot of the occurrence of nodes and edges for the whole graph. It cannot be said conclusively that this indicates the conscious development of the field in light of its earlier history, but it is very likely the case. When comparing the time at which new nodes enter the network with the time in which edges are formed, it becomes obvious that the formation of today's field first began around 2009 when a steep increase in the connectedness of the graph occurs, while the increase in nodes remains stable. Before 2009 most publications stand in relative isolation. Both the 2009 peak and a second peak in 2013 can be seen in the final panel of Figure 38 which tracks changes over time in the clustering coefficient.

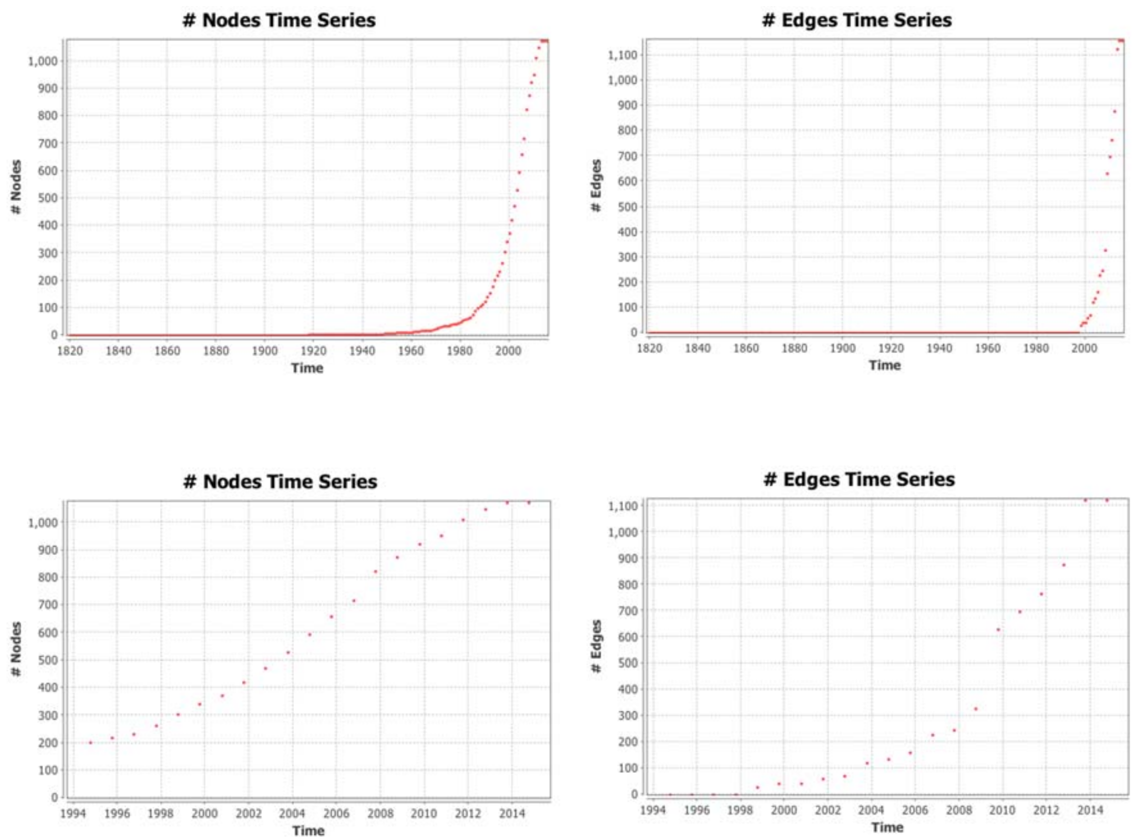


FIGURE 37: TIME SERIES FOR NODES AND EDGES

Given that connectivity, overall size, rate of growth, and regional spread, are continuously increasing, the question is less if the field is going to continue to grow, but how. Predicting the future growth of the network touches upon the question of preferential attachment (Barabási 1999). Throughout the sequence of graphs from figure 4 to figure 7, hubs of various sizes are clearly visible. Given the kind of knowledge network that is modelled, such a non-random topology matches the expectations of the dataset. In simple terms, those publications that have already attracted more attention are likely to continue to do so. Comparing the network evolution with the predicted development of scale-free networks in Figure 38, somewhat contradictory results can be retrieved. The graph for degree distribution shows strong linear tendencies and the formation of hubs are formed earlier than expected, which is reflected in a poor correlation between the predicted and the observed graph structure. The values for avg. clustering coefficient (and topological coefficients), however, show a better match between prediction and observation. Most back referenced publications before 1999 do not form hubs. After 1999 hubs form slightly faster than predicted by power law models. While the early history of the field shows a high degree of isolation from later developments, recent trends tend to strongly accumulate around hubs, which is likely to continue to influence the future formation of the field.

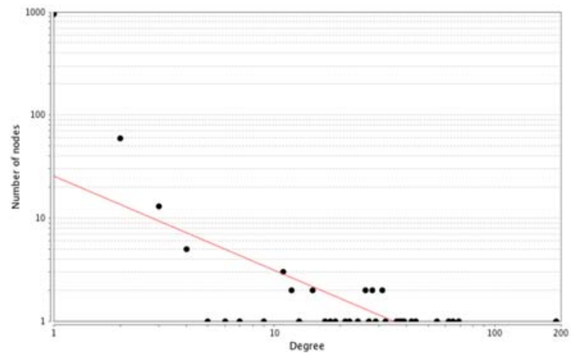
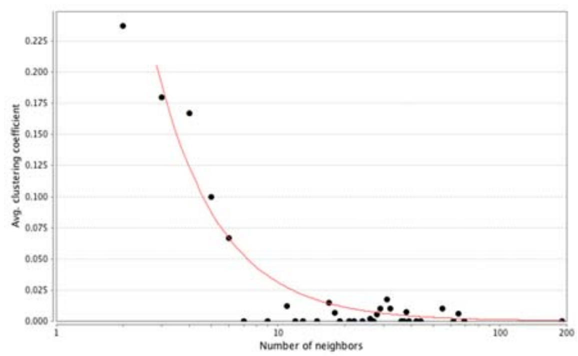
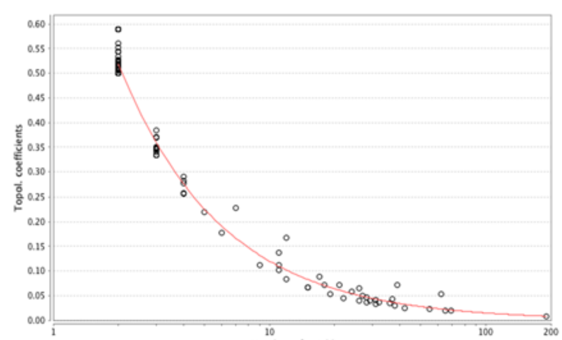
Correlation	**R-squared**	**Plot**
0.840	0.512	
0.957	0.803	
0.993	0.979	

FIGURE 38: PREDICTION (LINE) AND OBSERVED MEASURES (DOTS)

In summary, the network analysis shows a field with historic roots in the 19th century, experiencing intense spurs of growth and expansion. A high degree of ego-centric clusters impeded the formation of a truly connected whole characteristic for scientific communities. This, however, has been over-compensated in recent years, by a small number of publications that brought the fragmented parts of the network into contact. These brokers continue to unify the network to a higher degree than expected. It remains to be seen in the following section what the causes of their performance might be. The data at hand is not suitable for a detailed inquiry into the regional and institutional affiliations for each node in the network. While these are likely to have shaped the formation of the network, it is indicated and visualized that the internal structure of the network is exerting its influence. By drawing connection between otherwise disparate research endeavors, the modelled community indicates that it is now in a better position to formulate informed responses to methodological challenges, or to avoid repeating past mistakes.

4.4 TESTING THE MODEL

To test the model, additional data will be supplied to the NA reference list. This is an addition based on discussion and advice after a presentation at the international CAA in Oslo 2016. 4 additional articles were added to the core 37 per-reviewed articles to the sample NA dataset. All 4 additional articles are focused on answering cultural questions based on applied means of automatic feature extraction by remotely sensed data (FIGURE 39). This balances the weight between articles focused on technical or cultural questions within the dataset, but keeps the same skewness between data analysis approach of data versus model driven, and remote sensing by aerial imagery versus LIDAR.

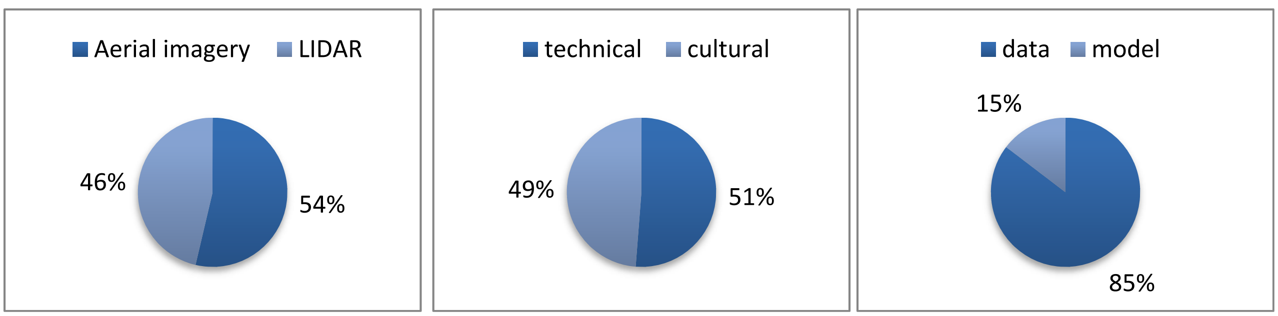


FIGURE 39: FOCUS WITHIN THE MODEL TESTING QUALITATIVE SAMPLE DATASET OF 41 PUBLICATIONS OF THE NA

The additional articles follow the same guidelines as the earlier dataset by not including papers with authors already within the dataset. This is done to keep the referential integrity, and not enhance individual bias and skewness to the dataset. The new dataset cannot visually replicate previous layout structure of the network, because when connectivity changes, so does the layout of nodes and edges. However, the patterns are discernible by same standard, and thus offer comparative analysis to validate or question the previous model. The new dataset consist of 1236 unique nodes by 1489 entries, giving 1367 edge relations in the network. In contrast the first dataset has 1075 unique nodes by 1277 entries, giving 1160 edge relations. This gives a slight increase in connection from 16% to 17%, and is an expected increase by adding more articles to the dataset. If continued, then the network will in the end be fully connected due to academic referential practice. However, it is not possible to referential investigate all literature ever published, so it is important to know how large the literary corpus needs to be in order to visualize a stable output, and to which degree more data is needed to be able to clarify academic connectedness. By four added papers it gives an increase of 7% to the dataset by total number of references, and it is therefore interesting to see if new patterns emerge (Figure 40). The top ten articles measured by centrality, do not change a lot with the added data (Table 10), indicating that both datasets are stable models of the community. Some changes, however, is necessary to mention. The top ten articles by centrality measurements remain the same, besides one paper being omitted by the added referential data, and that is the paper of Di Iorio et al. 2008. It previously had a high impact by PageRank, but has been completely pushed out in the new dataset. Despite that, the rest of the dataset remains stable, besides some slight changes in ranking brokerage by Betweenness and connectedness by PageRank. Di Iorio et al. 2008 had a high PageRank by having a very low degree of citations, but almost all being directly connected to one of the primary articles in the dataset, and that being of Di Iorio et al. 2010. But by the added articles in the new dataset, this bias weight is removed.

By Betweenness measurement, i.e. brokerage between authors, institutions, and fields, some slight changes occur in the ranking. Some papers are pushed out of the top ten, but still remain significant for the complete network analysis (Figure 40). Blaschke 2010, however, suddenly becomes very connected to the network by Betweenness measurement form in- and out-citations. This indicates that many of the new citations in the four added articles cite the same articles. Thus, Blaschke 2010 becomes an important broker of the field.

TABLE 10: COMPARISON OF TOP 10 BY CENTRALITY MEASURES (MULTIPLE APPEARANCES IN BOLD). SLIGHT CHANCES IN COMPARISON TO EARLIER DATASET

RANK	PUBLICATION					
	BETWEENNESS		PAGERANK (0.00…)		DEGREE	
1	*LAMBERS & ZINGMAN 2013*	190,5	BEN-ARIE & RAO 1993	…1057	BLASCHKE 2010	191.0
2	*BLASCHKE 2010*	182.8	***MOON ET AL. 2002***	…1019	SEVARA ET AL. 2016	82.0
3	*DE LAET ET AL. 2007*	179,3	TRIER ET AL. 2009	…0971	**BELGIU ET AL. 2014**	69.0
4	**MENZE ET AL. 2007A**	162	TRIER & PILOE 2012	…0959	ZINGMAN ET AL. 2016	66.0
5	***D'ORAZIO ET AL. 2012***	128,5	KRAUS & PFEIFER 1998	…0934	*LUO ET AL. 2014A*	65.0
6	FIGORITO & TARANTINO 2014	89,2	BRIESE 2004A	…0928	BHASKARAN ET AL. 2010	61.0
7	**BELGIU ET AL. 2014**	67	AXELSSON 1999	…0924	***D'ORAZIO ET AL. 2012***	55.0
8	BENZ ET AL. 2004	48,3	RUTZINGER ET AL. 2009	…0915	STOTT ET AL. 2012	49.0
9	*JAHJAH & ULIVIERI*	41,5	DEVEREUX ET AL. 2005	…0911	*LASAPONARA ET AL. 2014*	44.0
10	**MOON ET AL. 2002**	35	DUDA ET AL. 2005	…0906	**MENZE ET AL. 2007A**	42.0

The most important parameter for measuring the stability of the model is PageRank. The PageRank algorithm measures by neighborhood, and estimates value based on direction of edges to indicate influence on the field. The result is a probability distribution of the likelihood articles influence the field or are used to understand the field. The PageRank measurement remains stable, besides Di Iorio et al. 2008 being left out and replaced by Duda et al. 2005 in the top ten. As a result, both datasets are stable for modelling and visualizing patterns by. The visual layout of the network changes by edges, but the influence and brokerage of nodes remain similarly established between both datasets (Figure 40).

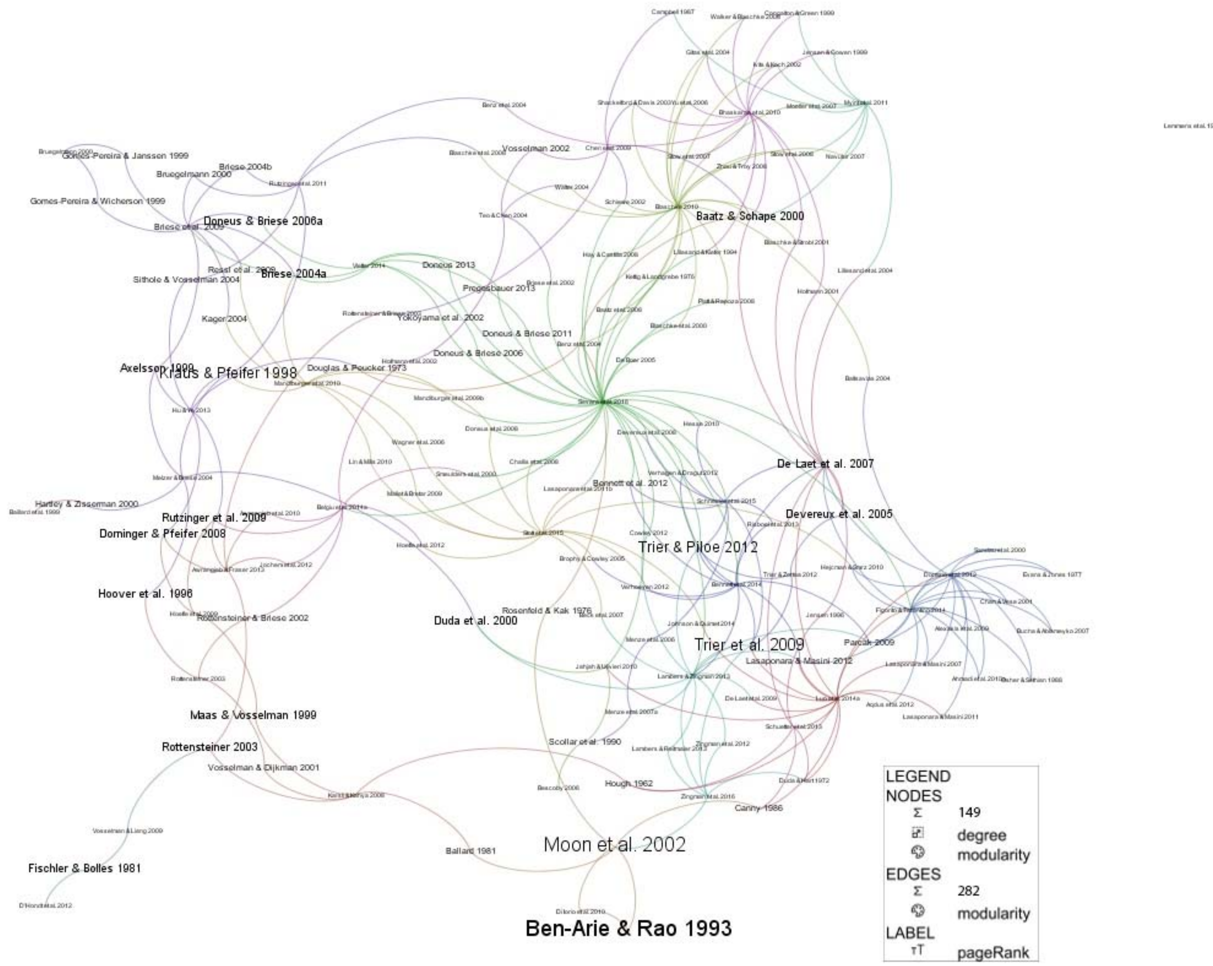


FIGURE 40: ADDITIONAL NA TO TEST THE MODEL

4.5 THE NETWORK IMPACT

Both NA and SLR point to the formation of a fast growing and increasingly connected discourse concerning automated procedures within archaeology. The analysis looks at the evolution of the field as it happens. This means that the network indicates that the community fundamentally trusts the praxis successfully spreading within the network based on selective pressures of standard academic review. What the method cannot provide, are a theoretical foundation for or against new paradigms. By 2009 a well-connected community starts to form, which is measured by the year of publication. The observable imbalance between model and data driven approaches, means that those following the majority approach had an advantage through a larger body of established knowledge. For the evolution of the field, it remains to be seen if model driven approaches can counteract this structural inertia, or if they continue to stand in relative isolation within archaeological practice to entirely different knowledge domains.

The overall focus (85%, FIGURE 39) on data driven approaches for both automated procedures and automated monument detection has shaped the development of the citation network. The dominance of procedures by unique proxy values and per-pixel analysis signifies a long-standing search for standardized means of detecting hidden monuments in vegetation. However, with LIDAR data this has changed so that both data and model driven approaches are applied to previously untested areas. Model driven approaches (15%, FIGURE 39) for automatic detection of monuments emerge in the mid 90'es, but with little immediate impact on the field. In this, the model driven community mirrors the data driven community around 1995 with many network isotopes and isolated nodes. More recently, it follows the general growth trend of a field consolidating itself. Looking at one example more closely, it may explain how innovations generate impact without forming connections in the graph. Arjan De Boer's work on standardized means of automated monument detection (2007), stands in relative isolation within the graph. Yet, despite its isolation, the methodological approach of De Boer (2007) regarding template matching and pattern recognition has found its way into the larger discourse of automatic detection and cultural heritage. This implies influence and collaboration from the field of computer science where these techniques are explored in depth under the heading of image analysis. The data lacks unambiguous references to research fields of collaborating authors, and therefore cannot accurately capture this implied influence. Our method can only capture innovation if it is expressed in the form of citations. Instances such as these are a reminder that knowledge advances along different trajectories during conference hallways, personal correspondences, and collaboration between fields. Future publications might still remedy this fact by forming new connections to earlier works.

From recent comparisons of best practice between model vs. data driven approaches, it can be seen that it is not a transition from pixels to regions, but rather two techniques towards the same aim (e.g. Brunelli and Poggio 1993; Myint et al. 2011; Pregesbauer 2013; Sevara et al. 2016; Tomljenovic et al. 2015). Consequently, a combined approach will likely set the next stage for machine learning. Machine learning is a versatile means for working with multiple variables and data sources towards optimized detection algorithms (e.g. Krizhevsky et al. 2012; Trier et al. 2016). However, it is only briefly present in the citation network by reference from the core articles, while machine learning for automated procedures for archaeological practice were not registered by the systematic literature review from our structured search queries. As with De Boer's example, lack of connectivity is neither a sufficient criterion for novelty nor does it preclude impact. Instead intellectual brokers can often only be judged in retrospect. In our case, the pattern of isolation is similar to that of data and model driven approaches ca. 1999 and 2010 respectively. Machine learning will likely evolve to form a discernible community with connections to both data and model driven communities. Looking at these patterns of isolation within the data, approaches combining all three elements are still insufficiently explored. Such combined approaches present promising candidates for future research implementation. However, the question is just as much then, whether it will be used within the archaeological community, and whether it improves the quality of detection by the gap of experience towards its potential target audience.

4.6 STATE OF THE ART FOR AUTOMATED DETECTION WITHIN LIDAR LANDSCAPES

To define state of the art for automated detection within LIDAR data is a matter of understanding classification possibilities and needs. Segmentation of data and landscape is common practice within remote sensing, but it is regulated by classification techniques that make for interest of investigation to determine best practice and state of the art. Classification techniques compose numerating and describing Cartesian space in order to contextualize pixels or geometries. The measured space can be translated as k-dimensional vector space where pixels are describing real world entities by points or pixels. The descriptors are spectral properties of reflectance, radiance, and transmittance or by combinational properties of geometry. Classification then becomes establishing a relationship between pre-defined class-categories, and unknown entities within the data. Whether state of the art is by data or model driven approaches is also questioned by Kamagata et al. 2005 and Sevara et al. 2016. Determining state of the art for automated detection in LIDAR data is also a difficult task because of the rapid development of the field. However, certain groups and advancements are influencing the field more than others, as can be seen by the referential dataset in the NA. A purely quantitative conclusion on state of the art by the NA is, however, not possible due to the rapid development of the field. Mainly this is because the NA looks towards the past by its referential structure, has difficulties of representing the present, and can only determine future if the future follows the same trajectory and pattern of the past. None the less, the NA models the development of the field, and helps us understand the field by visualizing actors of brokerage and influence. Qualitatively it is possible to determine relevant literature of the field by working within and understanding the field (e.g. Casana 2014; Lambers & Traviglia 2016). But by purely qualitative assessments, dangers are that the recommendations become much more biased than available by assessment through quantitative literary reviews, such as SLR and NA (e.g. Blaschke

2010; Tomljenovic et al. 2015; Agapiou & Lysandrou 2015). In the end, however, it is not one approach over the other, but rather combining both quantitative and qualitative means to determine state of the field and state of the art for automated detection by LIDAR and remote sensing in general. Otherwise the scope of the field of automatic detection for archaeological mapping, could easily restrain itself from getting input from new sources and other fields applying automated detection, by going into a spiral of closed connectivity. This is not a present day scenario, since it can be seen in the NA, that archaeologists are collaborating across many different fields towards improved positive detection rates within a wide variety of cultural landscapes. However, it is necessary to understand the trajectory of patterns within automated detection in order to recognize whether or not it is cultivating good academic practice and collaboration, or if the field is retracting towards secluded units of individual projects. Because, novel approaches requires continued support and attention from people of different perspectives. If not present, the field will end up in a struggle for large-scale cultural heritage management and detection, constantly taking two steps forwards, and one step back. In order to keep an open scope of perspectives, state of the art will be determined by a qualitative and quantitative assessment, as well as comparison.

Undoubtedly the wider archaeological community has recognized the potential and impact of automating procedures within remote sensing by segmentation and classification for archaeological management and prospection. However, using LIDAR created DEMs for automated information extraction is still rare within cultural heritage management and the archaeological community. In total four major research entities are identified within the NA, applying automated procedures for the detection of archaeological monuments within LIDAR data: Schneider et al. 2015; Sevara & Pregesbauer 2014; Stott et al. 2015; Trier et al. 2009. These are the core articles related to the four research entities. The aforementioned authors and co-authors stand at the forefront of applying automated detection by airborne LIDAR data within archaeological landscapes, and the influence they have on the wider community of remote sensing within the NA is differentiated by some leading and others following. The four research entities, however, do not constitute singular research entities, but rather symbolizing the core structure of collaboration within LIDAR based semi-automatic detection for archaeological landscapes. For applied automatic detection of archaeological monuments within LIDAR data, several other research entities also exist, but they do not exist prominently by in- and out-degree of reference, or by PageRank. Two examples of other important research entities and papers not present in the NA, are; De Boer 2007 and Vletter 2014. Equally, many other researchers work within the subject, but are not present in the NA in relation to the criteria of applied automatic detection of archaeological monuments within LIDAR data, but will be products by reference in future NA investigations due to the conclusions possible to produce by SLR and NA. The implementation of automated information extraction within the archaeological community is greater and more established with a wide variety of applications by both data and model driven detection. The field is also constantly expanding with many new authors emerging and establishing themselves by applying detection algorithms within LIDAR data (e.g. D'Orazio et al 2015; Freeland et al. 2016). However, the four defined research entities are the present communities validated within the NA by citation. From these four research entities, validation for best practice can also be established and investigated, and whether or not best approaches are data or model driven. Three of the four, Schneider et al. 2015; Sevara & Pregesbauer 2014; Trier et al. 2009, apply model driven approaches. One research entity, Stott et al. 2015, focus on data driven approaches. The initial work on automated archaeological monument detection was carried out by Lemmens et al. 1993, but does not have a significant presence within the NA, despite also being used as one of the core articles within the NA. Equally so, Redfern 1997 and Redfern 1998 also have no presence within the NA, despite its undoubted impact on archaeological cognition for digital landscapes. However, both Lemmens et al. 1993 and Redfern 1997 focus on satellite and aerial imagery, and Lemmens et al. 1993 combines early attempts of both a data and model driven approach. To a large extent, most of the remote sensing community by satellite and aerial raster is focused on data driven approaches, i.e. by pixel value and per pixel segmentation, but great strides are also taken for object-based approaches for satellite and aerial raster to overcome data driven approaches targeting the singular pixel for statistical analysis, and instead produce complete non-overlapping segments or polygons (Blaschke 2010, 4). Data driven approaches, are geared towards producing segmentation algorithms to divide raster into relatively homogenous segmented significant groups of pixels. However, this pose a problem when dealing with heterogeneous archaeological structures and features revealed as remains after hundreds or thousands of years of decay and deconstruction. Meaning, the archaeological remains rarely compose homogeneous segments of landscape, but rather adaptations to wear, tear, and natural, cultural, and geomorphological impact. Naturally, this is affecting all means of information extraction from archaeological remains in the landscape, and as such defines the ambiguity that is present in all aspects of the archaeological practice. In the end, it is therefore a question of what is more successful. The interesting aspects become conclusions based on time efficiency, cost efficiency, use and quality of end results. Time efficiency is related to computation and know-how. Cost efficiency associates with data acquisition, as well as software and hardware needs, which in return has a direct effect on use by the community. The end result is quality of information, which is indirectly impacted by quantity of use and experience gained within the community. These four parameters help evaluate conclusions of state of the art, and can be comparatively assisted by results of the NA. Evident is the presence of Øivind Due Trier and his team through multiple publications on the subject of automated information extraction by LIDAR data (Trier et al. 1996; Trier et al. 2009; Trier et al. 2011; Trier & Pilø 2012; Trier & Zortea 2012; Trier 2015; Trier et al. 2015; Trier & Huseby 2016; Trier et al. 2016). The two articles Trier et al. 2009 and Trier & Pilø 2012 has particular impact on the community by its ranking in the NA, as well as by its qualitative recommendation of state of the art value referenced by other articles describing the field. However, the above mentioned articles and the Norwegian research collective, are not simply applying one method, but rather experiment by both data and model driven approaches towards information extraction from many different sources of remotely sensed data. What this pattern exemplifies, is similar to the pattern seen within the entire community of automatic detection, as that of experimentation, innovation, and exploratory investigation towards understanding and defining best practice and state of the art. Thus best practice and state of the art is not as easily defined, because of its dependence on data and context, but even more so by the rapid development of methods for digital manipulation of data and information extraction. The research entities applying automated procedures for the detection of archaeological monuments within LIDAR data are focused on model driven approaches by geometry extraction and template matching. However, the majority of articles within the NA, and within the field of automated detection of archaeological monuments within remote sensing, are focused on data driven approaches of segmenting landscape and extracting information. This is directly correlated to investigated data, resulting in raster data processed by data driven approaches focused on the visual spectrum of details. Meanwhile, model driven approaches are more commonly used on spatial data such as LIDAR. Especially the approach of template matching, and geometry matching has taken a significant position for automated and semi-automated extraction of archaeological data in landscape. Best results of automated and semi-automated detection of cultural heritage specific questions are papers with a high page-rank. High page-rank papers inspires and leads the field, while brokers tie the field together. Thus, high page-rank papers will commonly be papers of best practice based on given time of publication, while brokers inspire the field to reveal high page-rank papers. Naturally, this is just a representation of how the field has formed, used, and might inspire, but in reality not necessarily define best practice going forward.

So the question then becomes: is the future of automated information extraction within archaeological LIDAR either data or model driven? As previously stated, the future should perhaps not be determined as one approach instead of the other. However, in order to define a trajectory from which to improve from, it is necessary to understand best possibilities in the present. By assessment through necessities of time efficiency and quality, large-scale landscape investigations for archaeological use might not be implemented by its ability to incorporate multiple variables, but rather by its ability of application within the archaeological community. As Parcak is also asking: "*Is satellite technology advancing faster than archaeologists' ability to learn, apply, and analyze the data and programs, and all the inherent implications*?" (2009, 239). A simple answer to this, and as indicated by the SLR, is that semi-automatic and automatic methods are not represented within archaeological practice. The NA on the other hand visualizes a growing community within the archaeological community adapting to new methods and techniques for handling the data explosion within cultural heritage management. To tackle the taboo of automation within cultural heritage, it is necessary to stay open-minded and see the possibilities of improvement and aid gained within the short time of existence within archaeology (Bennett et al. 2014). The academic practice of peer-reviewed publishing slows down the process of information sharing, and thus case-studies and smaller projects can often be several years older than the date of publishing (Parcak 2009, 239). For more rapid development of the community and information sharing, new means for publishing the results are necessary. This could be by open online journals by simpler or other standards than customary academic journal papers to reduce time interval between case-study results and actual publication, as well as give way for more specialized research towards direct exchange comparison and quality control by the community. However, the impact of LIDAR and model driven approaches of processing data for archaeological segmentation and information extraction, is both increasing in influence and significance in recent years. Consequently, primary approach for computational semi-automated information extraction will in the following chapter be focused on model driven approaches of information extraction by templates. However, first and foremost, to determine success parameters and the future of automated detection of archaeological monuments, it is necessary to investigate applied means of automated and semi-automated information extraction from LIDAR data by model driven approaches. This will be elaborated in the following chapter, **APPLIED DETECTION IN LIDAR DATA**, as to evaluate application and compare both computational and human interpretation by micro and macro pattern recognition within an archaeological landscape.

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5. APPLIED DETECTION IN LIDAR DATA

The possibilities of automated detection for archaeological monuments are numerous, but most are built around commercial software packages offering a range of applied means of segmentation. However, image and feature analysis is equally developing by open principles of code and library sharing towards improved information extraction. Many are shared and offered as singular code string, code libraries or plugin extensions for open-source software packages. By using partly or completely open-source code and software, the application possibilities are equally numerous. But what are the application possibilities for large-scale archaeological mapping in the digital landscapes of LIDAR data? Almost all GIS and image analysis software offers some sort of data segmentation, but for archaeological mapping and detection the results are often highly limited or simplistic due to the degradation, decay, and imperfection of archaeological data. The applied means of automated detection draws on the history of image processing by vegetation indices (Shennan & Donoghue 1992) and Tasseled Cap transformation (Kauth & Thomas 1976) in satellite imagery by transforming original image bands into new converted image bands. Applied detection in LIDAR data, however, diverts from data driven spectral values to dimensions of shape and model driven approaches. This was also seen by three of the four leading and influential research entities identified in chapter 4 by focus on spatial dimensions of LIDAR data to extract information. The search for homogenous values and indices visualizing archaeological features and structures across different landscapes is still ongoing, but so far, no single variable is capable of depicting the diverse and heterogeneous cultural impact in and on the landscape. This results in the necessity to involve multiple variables to extract archaeological information in the landscape, even for earthworks and monuments shaping the landscape. The complexity of information extraction from remotely sensed data complicates the possibilities of scaled investigations and the implication of resolution in large-scale investigations for archaeological mapping. The quality of information from remote investigations is correlated by intensity and involvement of investigation, since a measure of ground truth is compulsory to all novel remote investigations. Thus quality of information is undoubtedly directly connected to invested use or work, while amount of work is dependent on investment by cost and time efficiency. Thus, in order to improve quality of information, it is a matter of cost and time efficiency regarding detection of archaeological monuments in LIDAR data. Since a certain degree of verification by field inspection is necessary to determine ground truth, it is essential to define a balance between desk-based investigations and fieldwork for more quantifiable truths from which digital and analog details are correlated and comparable (Cowley 2016, 148; Sevara et al. 2016, 496).

5.1 TWO METHODS OF INFORMATION EXTRACTION

The two methods for information extraction of archaeological monuments within remote sensing are by either data or model driven approaches. Meaning, they either extract information by per pixel or entity. Within both methods are different possibilities of investigation from smallest entity contained within data by per point, or by grouped attributes in entity. This, in return also has an impact on range of application by scale, since computation and comparability changes according to dimension of investigated entity (Risbøl et al. 2013; Trier & Pilø 2012; see also chapter 2.9). By investigation of smallest entity and per pixel value, different landscapes need altered means of manipulation. By information extraction from grouped entities, the shape detected in local context results in potential comparison between results from different context. Thus, using a model driven approach, structures and features detected can be compared in a wide variety of landscapes, because the information extraction procedure is analogous. Using a data driven approach, however, the increase in variables implies that methods needs to be altered between different context and landscapes, i.e. flat and sloped landscapes, as well as by frame of a more or less manipulated landscape. This, however, also means, that any feature detection within a given landscape can be improved by data driven approaches due to its near infinite amount of potential variables. A near infinite amount of potential variables to describe and quantify landscape also implies heavy computation and complicated contextualization. Hence, initial information extraction is more easily achieved by model driven approaches to minimize computed area. The virtue of LIDAR data is its dimensionality by elevation, but the emphasis on geometry is also due to the often lack of spectral information in LIDAR data, i.e. color, near- or infrared wavelengths. As specified in chapter 2.6, this is likely not a restriction of future LIDAR datasets incorporating multiple wavelengths towards increased variables of digital landscape information (Stott et al. 2015), but it is the present premise of most LIDAR datasets. The value of LIDAR data is its capability of depicting terrain instead of surface, and spectral information of the terrain is not as imperative as spectral information of the surface towards use and information extraction. The spectral values of the surface are more easily recorded by aerial and satellite imagery, but can also be of value to LIDAR data in future perspectives. Presently it is a matter of cost and time efficiency when choosing which method to use for recording terrain or surface in the landscape. Naturally, the methods can be combined, correlated and draped in order for LIDAR data to depict the spectral values captured by aerial and satellite imagery (Rowlands & Sarris 2007) as shown in FIGURE 41 of burial mounds east of Stockstadt. Draping does not necessarily increase information extraction, but improves how to cognitively understand the landscape correlation between terrain and surface (FIGURE 41).

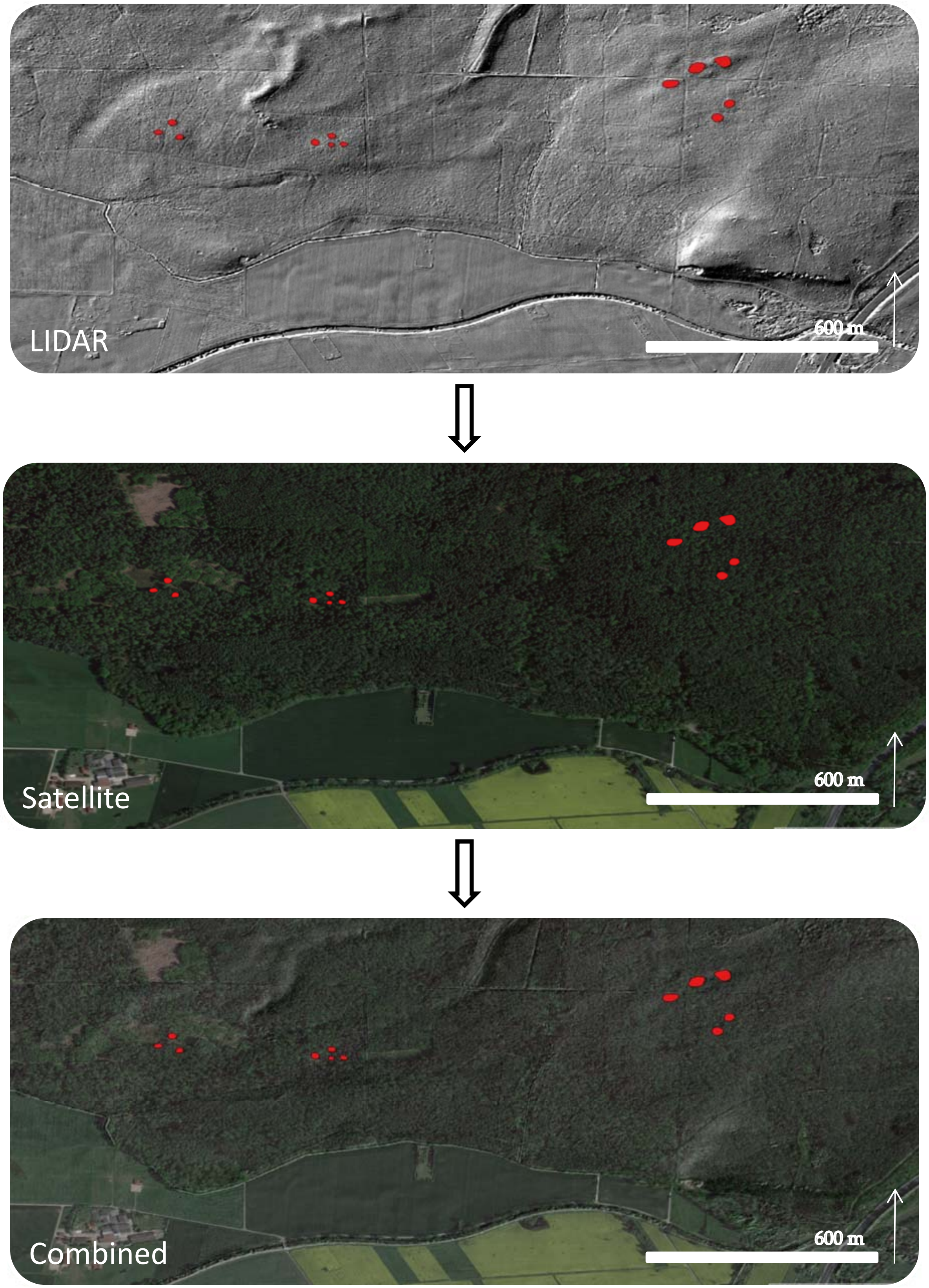


FIGURE 41: ADDING SPECTRAL VALUES BY DRAPING SATELLITE IMAGERY OVER LIDAR DATA TO HELP PLAN AND INTERPRET LANDSCAPE. SHADED RELIEF: AZI. 45°, 270 ANGLE. SAT. RASTER: © GOOGLE EARTH

Added spectral information recorded in the LIDAR point of surface and terrain by mounted camera, is different than the combination of LIDAR and aerial and satellite raster data, but offers some of the same possibilities. Terrain is not represented in color by combination of LIDAR with aerial and satellite raster. Nor is it present in the LIDAR return signal from surface and terrain. Color in the LIDAR point is not documented by emitted active signal, but by the passive wavelengths in the landscape by a mounting combination between of different means of documentation. Meaning, the LIDAR point is constructed as a combination of recorded raster values of landscape and the energy recording of return signal in space and signal strength. Therefore, spectral information of terrain is always obstructed by canopies in the surface, resulting in limited separability of the color scheme of the landscape (Brodu & Lague 2012; Lichti 2005). Spectral information is recorded in a pixel or point, and can be individually extracted as visualizing certain tendencies in landscape. This is commonly extracted by data driven approaches. Model driven approaches are the segmentation of information in entities, rather than by individual attributes. However, it is calculation focused on individual attributes and pixels in order to segment into Areas of Interest, AoI. This is performed as segmentation methods of point-based, edge-based, or region-based techniques (Schiewe 2002). The pattern of interest can be certain distribution patterns of points, edges, or patterns of shape to extract entities. Equally, all detection is the extraction of clustered, ordered, random or patterned discrete and continues data variables (Figure 42). Computational detection by shape is segmentation and/or classification by combined rules of extraction and interpretation.

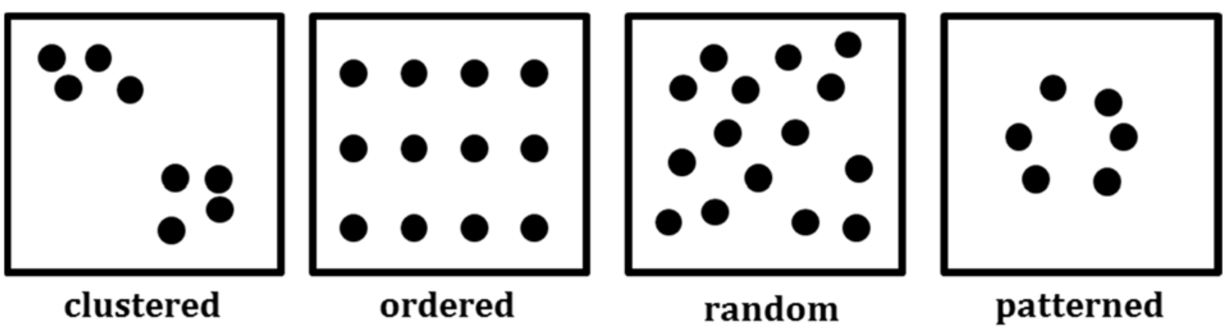


FIGURE 42: DATA ORDER REPRESENTED BY POINT DISTRIBUTION

No image segmentation is capable of representing the cultural landscape completely for archaeological investigation, but segmentation attempts to provide meaningful non-overlapping entities in images. They are either pixel or model driven, and visualize based on input criteria from statistical analysis, homogeneity, textural, geometrical, contextual, and prior knowledge. The result is classification based on segmentation of belonging to a classification category, and equally so not-belonging.

5.2 HIERARCHY OF INFORMATION EXTRACTION

The means of information extraction is by either segmentation or classification. Segmentation splits context according to a given criteria, e.g. presence or absence and the confidence value or scale in-between. Classification is the addition of information if a given criteria is met, e.g. minimum z-value classified as terrain and anything above as surface. Segmentation and classification can be done, manually, semi-automatic or automatic based on interaction before, during, or after computation by given criteria. It is therefore a constant of two approaches on how to extract and compute information from data input towards data output, and to which degree data processing best suits the queries given. However, the notion of a fully automatic system of documentation would require both automatic segmentation and classification with a correct positive feature return. This is rarely the case in archaeology because of imperfection of monuments, and the necessity of validation by results and conclusions. Thus, for computational cultural heritage management, a system will always be that of a semi-automatic process due to the adaptation to context, the state of archaeological monuments, and the lack of adaption to scale and differing patterns by scale (Risbøl et al. 2013). Algorithms and code attempt to define rule based learning adaptations to improve detection rates. However, the archaeological structures and features are difficult to construct as defined rules due to diverging patterns. To adapt to scales of perspective, Neural Networks, NN, are necessary to introduce a hierarchy of investigation. NNs are trained on sets of dependent output variables measured on known input to find linear fitting mechanisms to find regularities on given dataset (Barceló 2009a, 16; Barceló 2009b). To compensate for strict rule based approaches of NN, Artificial Neural Networks, ANN, are constructed as an information processing paradigm set to mimic the human brain cognition by interconnected non-linear processing elements to accept numeric input in unison towards numeric outputs. Raster data is easily transferable as numeric pixel input, or vector input calculated by per pixel, and thus transferred to NNs and ANNs. Archaeological observables and archaeological explanations are no longer represented in terms of sentences, but as numbers. This allows intelligent processing of archaeological data (Barceló 2009a, 16). Redfern (1997) arranged an ANN to create algorithms for comparison of vector geometry as unsupervised object classification, but despite initial interesting results, the approach has not had a real impact on feature detection and information extraction within archaeology. This is not until recent attempts by the Norwegian Directorate for Cultural Heritage and the Norwegian Computing Center to construct Deep Learning by Convolutional Neural Networks, CNN, showing some interesting aspects to construct rule based approaches for information extraction of linear features, i.e. roads, pathways, terraces, and similar features (Salberg et al. 2017).

NNs undoubtedly have a great potential for pattern recognition. The reasons for a lack of impact on the archaeological community are most likely problems with applicability through know-how, but also due to the necessity of detection by rules of properties and variables. Because idealized archaeological monuments rarely exist, resulting in the range of exception being as great as the range of application. Thus, parameters of potential use through quality of information and time and cost efficiency are the limiting factors for application within the archaeological community. In the end, the complexity of the cultural landscape requires as many exceptions as rules to navigate. Hierarchies of information extraction and manipulation in NNs are therefore incomplete, while ANNs intrinsically distance itself from the archaeological sphere of acceptance and certainty by the complexity to improve quality of information by validation. The partial visibility of archaeological features and structures in the terrain, often resolves in the distinction between individual pixels being too few to segment between area of interest, and area of non-interest. Equally, automated information extraction is as much a discussion of acceptance and certainty as a discussion of ground truth detection. Meaning, it is a matter of segmenting and classifying landscape to a degree from which detection rates can be accepted as improving quality of information and cost and time efficiency compared to human cognition and interpretation. This is because, automated information extraction is only valuable if it aids and improves any means of the process for cultural heritage detection and management. Automated information extraction benefits our understanding of remote sensing by quantifying landscape and the features and structures within to standardize input and output. But, despite the algorithmic steps and rules being potentially imperfect and complex, automated information extraction offers a possibility of altering pattern perspectives for segmentation and classification. Thus, it is matter of finding application aiding and improving the archaeological agenda for standardized and quantifiable possibilities of analyzing digital landscapes. Unique values for detection of archaeological monuments in digital landscapes do not exist, but rather a range of values depict different correct information extraction for cultural heritage detection and management. So far, the most influential applications are model driven approaches, as concluded in chapter 4. Equally, algorithmic complexity do not necessarily offer the best approach for application within the archaeological community due to the need of simple and repeatable methods of automated information extraction and pattern recognition (Wheatley & Gillings 2002). Therefore, the point of departure needs to be simple automated information extraction aimed towards broadest audience possible in order to establish lasting impact on cultural heritage management and detection.

5.3 SIMPLE INFORMATION EXTRACTION

Model driven approaches of information extraction can be calculation of correlation between entities and templates on data. Data driven approaches calculates local details by per pixel or cell. Both are simple forms of data extraction. Model driven approaches remains simple, whereas data driven approaches can be near infinitely complex by complementing variables and variable range. Thus, model driven approaches are close to a finite potential, whereas improvements are enhanced by data and per pixel based calculations to near infinite variations of features and structures based on context and landscape. However, this complexity equally makes for information extraction not being simple, and thus not necessarily improving the quality of information. Simple information extraction therefore has strengths for the archaeological community, especially in regards to effective impact on use. The implications being that the archaeological community should remain focused on simple matching algorithms for best cost-benefit of input and output (Bennett et al. 2014, 901-2; Grøn et al. 2011, 2030). Simple information extraction is not only done by automated detection, but also by manual visual detection. The standard for interpreting landscape is done by visual inspection for cultural heritage management and detection. Visual detection is a very efficient and important procedure of interpreting landscape, and equally has great potential for aspects of crowd-sourced data for large-scale landscape analysis to improve the scale of investigation (Duckers 2013; Goodchild 2007). However, automated procedures for segmenting and classifying landscape do not exist as a replacement for manual visual detection, but offers improved or complimentary visual representation to interpret landscape. Simple information extraction by well applied segmentation and classification offers a procedure of application usable by the larger archaeological community to improve qualitative and quantitative investigations, as well as standardizing procedures for comparison and verification. Thus, automated information extraction is equally interesting by its improvement for visual detection. Naturally, a simple segmentation and classification does not necessarily produce more accurate detection rates, because the range of variables used are limited by the need of simplicity and transparency. Therefore, it is a question of use and possibility of application when compared to centralizing procedures of automated cultural heritage management and detection. Because, the quality of information is constructed by inductive interpretation and confidence to understand application in order to be accepted and standardized, and thus claim methodological value for the archaeological community. Transparent applicability is therefore the key necessity. Transparent applicability can be argued to be at the core of model driven approaches of automated information extraction, because the premise is similarity and brute force matching. Brute force matching compares variables and matches with all other features in given input and dataset. The matching algorithm of variable and feature definition differs based on methods and equations, i.e. best match or best match to *k*-means clustering to *n* partition. The principle, however, remains similarity comparison. Similarity comparison follows the *simple matching coefficient* of similarity and dissimilarity (EQUATION 3).

EQUATION 3: PRINCIPLE OF SIMPLE MATCHING COEFFICIENT FOR DATA MATCHING

$$smc = \frac{A\ (matching\ values)}{B\ (values)}$$

$$smc = \frac{\leq 1)}{1}$$

$$smc = \frac{3+4}{3+4+1+2} = \frac{7}{10} = 0.7$$

The equation above is a calculation of similarity and dissimilarity, but towards binary presence or absence by numeric 1 or 0. The principle follows quantitative comparison between both model and data driven approaches of similarity detection by binary calculation of pixels, cells and numerical representation. Within 0 to 1 there is a binary representation of presence or absence, but also the infinite representation of scale by the decimals leading to 1. Consequently, from 0 to 1 constructs the potential of infinite variations, but equally a finite representation as defined by given thresholds of segmentation. Classifying the finite thresholds, however, requires limitations to the infinite space, meaning a compromise on infinity is necessary to represent classification. Likewise, any similarity detection is a matter of compromise to define thresholds or variables capable of equating input comparison by reasonable confidence in output. Segmentation is defined by the threshold of partition by given value, from 0 to 1, and thus specifies and outlines resolution possible for classification. Brute force matching by simple shape comparison offers several improving benchmarks for remote investigations for the archaeological community, not least by the ability to use output to segment input into macro patterns of more discernible information for the interpreter. However, archaeological data is by nature imperfect and thus not possible to distinctively partition as binary, unless extensive compromise of data representation or value is given. Meaning, in understanding the objects, features, and structures of the past, nothing is completely similar, but everything a compromise towards similarity labels or representations. Even brute force matching cannot remain simple information extraction, but rather qualitatively defined on a scale of infinite variations from 0 to 1. Simple information extraction, therefore, does not stay simple unless it is constructed to follow gradual compromise. Similarly, the application of brute force matching is by virtue computational simple, but computational processing can be excessive if iterations are made on large quantities of data. The concluding output of any algorithmic chain of operations can equally be excessive and intricate to a degree where it is not improving invested quality of information, thus defeating the purpose of automating steps of computation. It is therefore a matter of finding standards of automation that improves cost efficiency and quality of information. In order to do so, it becomes essential to understand and compare between manual visual detection and automated information extraction. For this task, a focus group was formed to compare visual detection, automated information extraction, potential coverage, pattern understanding, and concluding quality of information. This will be represented in the following sub-chapters; **5.4 Visual Detection; 5.5 Crowd-sourced visual detection; 5.6 Computational mound detection by templates; 5.7 Comparison between crowd-sourced data and template matching**

5.4 VISUAL DETECTION

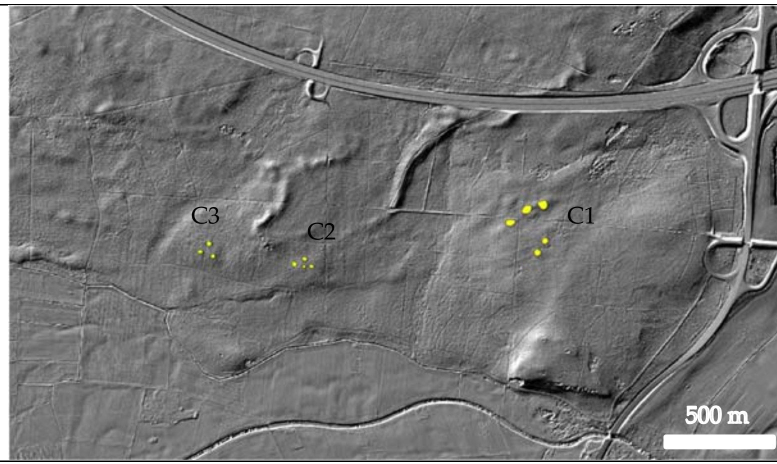
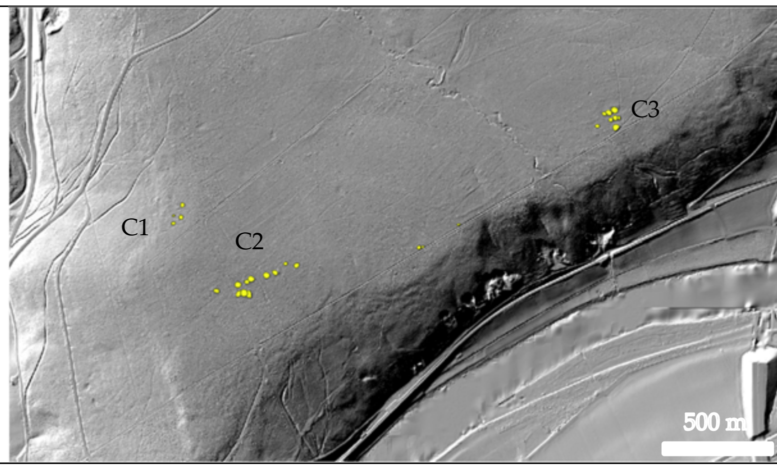
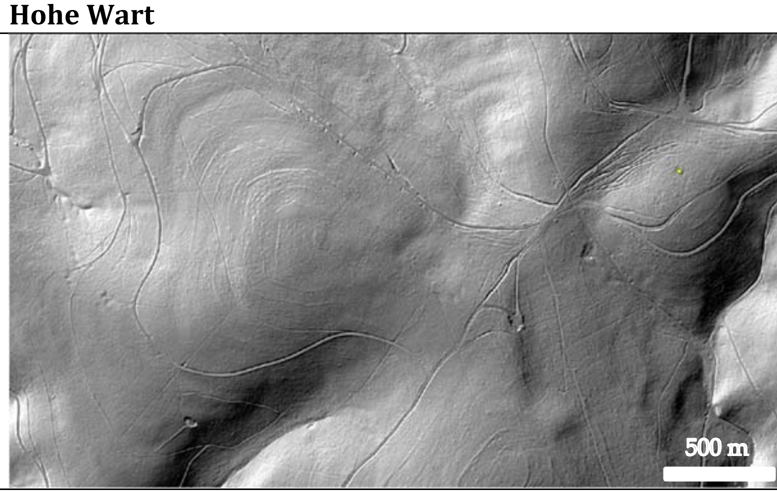
Visual detection is manual detection by human interpretation and cognition. Human cognition is relatively well adjusted and adapted to distinguish and discard on the scale from similarity and dissimilarity in any given context. This also applies to micro and macro pattern detection within digital landscapes of remotely sensed data. Equally, patterns of nature and patterns of culture ranges from being similar and dissimilar, however, human cognition adapts to scaled macro patterns, and thus focusses on more than the individual micro contrast or shape. Therefore, even inexperiencedvisual detection can derive reasonable detection rates by crowd-sourcing. This is also evidenced by the studies of Gary L. Duckers (2013) on web-based interpretations on remotely sensed data between a professional group of archaeologist and a group of inexperienced volunteers. Complete and constant coverage of landscape for archaeological heritage management, requires cost-beneficial visual detection analysis based on crowd-sourcing information from a wide variety of groups (Goodchild 2007; Simpson & Williams 2008). Surveying by crowd-sourced visual detection resulted in an average coverage of around 4.7 km^2 per day by an experienced professional group, whereas the inexperiencedgroup of volunteers surveyed around 5 km^2 per day (Duckers 2013, chapter 4). This does not necessarily indicate uniformity in the quality of information from the transcription of remotely sensed data. Comparatively, the survey areas covered by crowd-sourcing from experienced and inexperiencedfocus groups are almost similar in comparison to spatial area investigated. Open data and open investigations therefore has advantages in regards to amount of possible area and amount of information extracted. The potential amount of information is increased by crowd-sourcing data from interested groups and people by the sheer number of potential surveyors enlisted. Thus, a large body of inexperienced investigators has the potential to locate almost all details of interest within a landscape, despite not necessarily having the same prerequisite to make initial detection compared to expert investigators. The potential detection is the same between experienced and inexperienced investigator, but the confidence in quality of extracted information differs. The question then becomes, is the quality of information as a result better or worse? Answering this is not simple, since there is no singular measure for correct detection of all cultural heritage information hidden in the landscape. The range of information hidden in the landscape constantly changes by smaller and larger impacts on the landscape, and the patterns are different compared to resolution and scale by perspective and source. Therefore, the outcome is not only determined by the remotely sensed data, but rather as a perspective and source of interpretation. Amount of data detail and resolution indicates potential amount of information from macro and micro pattern detection. But, amount of detail and information by resolution, does not guarantee complete detection, as discussed previously in chapter 2.9.

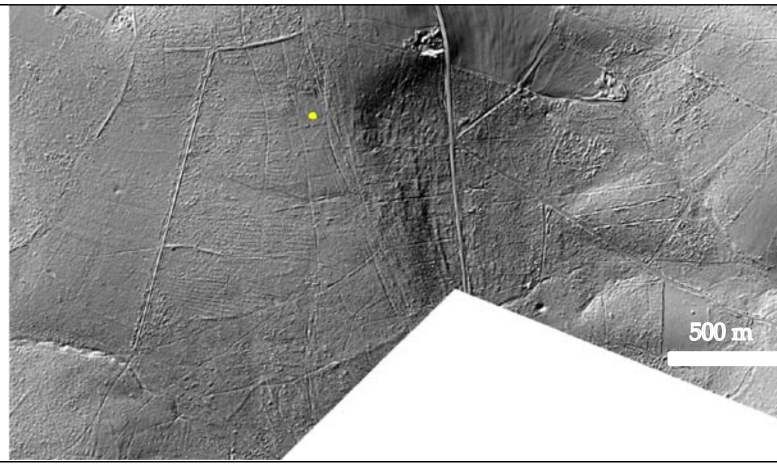
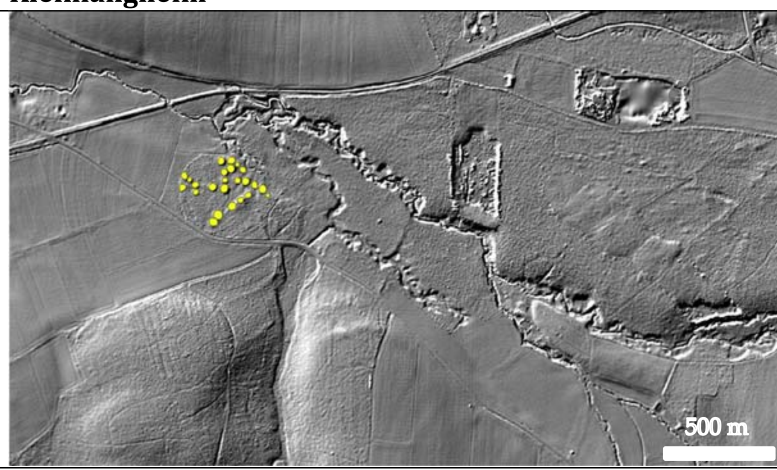
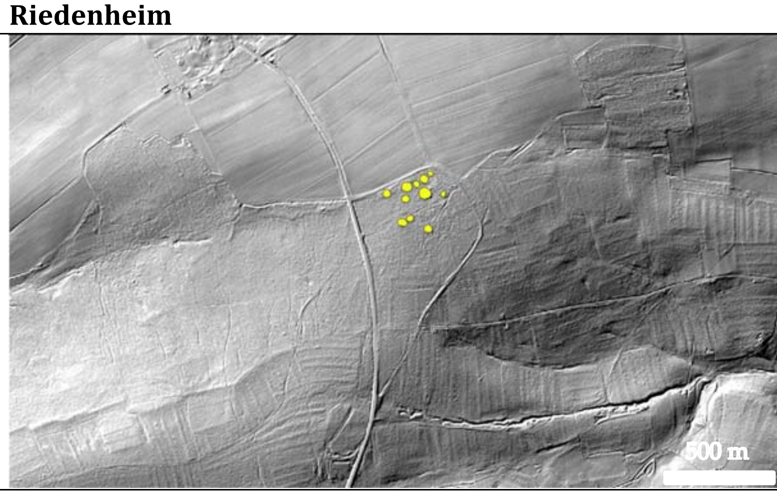
The potential within remotely sensed data can be improved by automated means of segmenting and classifying landscape for inspection by both experienced and inexperienced groups for quality of information verification. Undoubtedly, there is a difference in quality of information between experienced and inexperienced surveying, but this can be negated by the amount of investigators aiding visual detection by combined information extraction and the combined confidence value constructed by repeated detection. Naturally, bias plays an integral part of the human brain for both experienced and inexperienced investigators, resulting in classification by expected outcome rather than by open unbiased interpretation. This can lead to homogenous wrong detection patterns (Bennett et al. 2014, 899), but is similar for automation which focuses on detection by experienced, known, and defined patterns. To understand some of the problems and solutions, it is necessary to qualitatively and quantitatively exemplify by revealing patterns of detection from human and machine interpretation of landscape. Human and machine interpretation of landscape is investigated and compared by the nine selected sites for evaluation by visual detection and empiric ground truth verification (see chapter 5.7), crowd-sourced visual detection by inexperienced groups (see chapter 5.5), and automatic detection by template matching to compare and enhance detection confidence (see chapter 5.6). The following consist of initial visual detection and ground truth verification. The surrounding area have been systematically surveyed, but only if details in the landscape by visual detection demarcated areas of interest or potential interest. Meaning, some areas within the nine selected sites have not been systematically surveyed, and can still include additional information of interest. However, the visual detection and ground truth verification revealed 108 burial mounds in different types of landscape at different locations in Lower Franconia (TABLE 11). At each individual site the clustering of burial mounds varies greatly, and some burial mounds are located completely isolated (TABLE 12). The mound chronology is mainly determined by pattern, shape, and potential contextual relation to sites in the vicinity and material culture found in the surface and topsoil. The result of this is, that the temporal and cultural frame is for most of the sites unknown and simply classified as unknown prehistory (see appendix 3B).

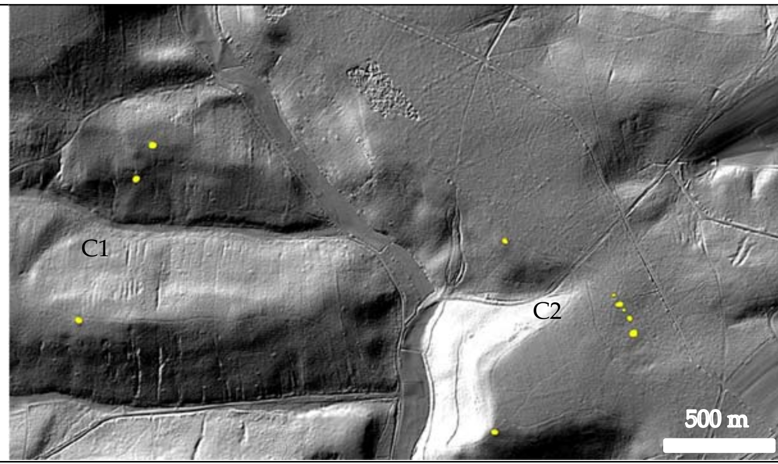
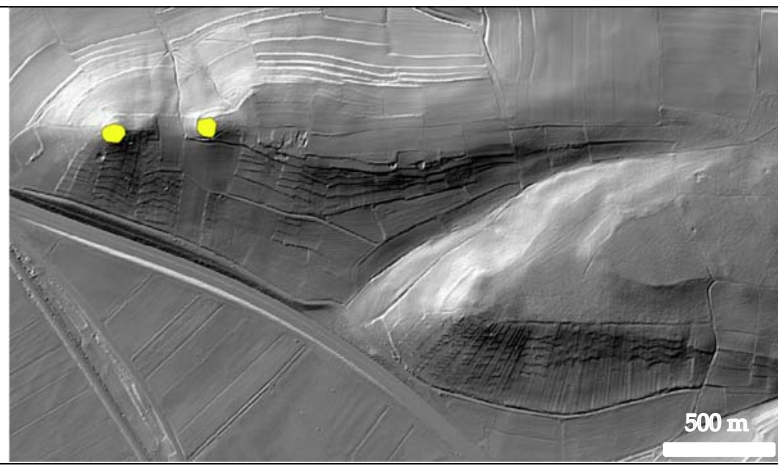
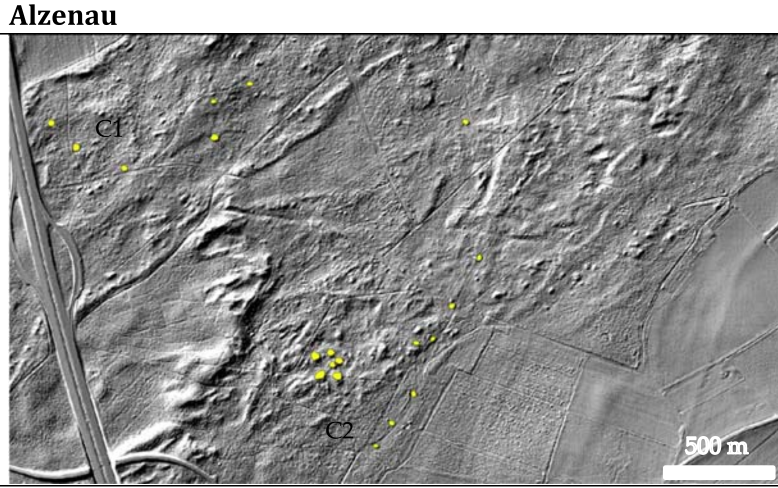
TABLE 11: NINE SITES FOR SAMPLING COMPARISON

No.	SITE_name	Amount verified
1	Stockstadt am Main	12
2	Triefenstein	25
3	Hohe Wart	1
4	Amorbach	1
5	Kleinlangheim	26
6	Riedenheim	11
7	Maroldsweisach	10
8	Stettfeld	2
9	Alzenau	20
		108

TABLE 12: THE NINE SELECTED SITES WITH VECTORIZED MARKING OF EXACT BURIAL MOUND POSITION

NAME	**Stockstadt am Main**
Burial mounds confirmed by field inspection: 12	
NAME	**Triefenstein**
Burial mounds confirmed by field inspection: 25	
NAME	**Hohe Wart**
Burial mounds confirmed by field inspection: 1	

NAME	**Amorbach**
Burial mounds confirmed by field inspection: 1	
NAME	**Kleinlangheim**
Burial mounds confirmed by field inspection: 26	
NAME	**Riedenheim**
Burial mounds confirmed by field inspection: 11	

NAME	Maroldsweisach
Burial mounds confirmed by field inspection: 10	
NAME	Stettfeld
Burial mounds confirmed by field inspection: 2	
NAME	Alzenau
Burial mounds confirmed by field inspection: 20	

The nine selected and surveyed sites constitute good sampling variability for evaluation of manual and automatic detection potential. Equally, the nine sampling sites consist of landscape in the range from simple to complex landscapes of curvature, as well as demonstration of human and natural manipulation and impact on landscape terrain and surface. However, at the site of Alzenau, the wandering sand dunes in the surrounding area of the two burial mound clusters, makes for very insecure verification. However, it is certain that two burial mound clusters are present, but also at very different degrees of preservation. Generally, the burial mounds within each and every sample site are in different stages of preservation, and in diverse contexts of homogeneous and heterogeneous curvature of landscape. The clustering of burial mounds within the different sites also alters according to past and present cultural impact, meaning that different perspectives of micro and macro patterns are necessary for a comprehensive interpretation and classification of individual burial mounds, as well as burial mound clusters.

5.5 CROWD-SOURCED VISUAL DETECTION

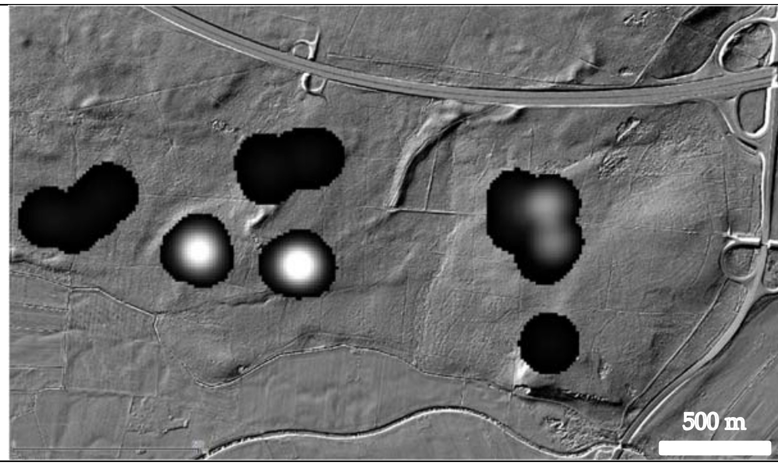
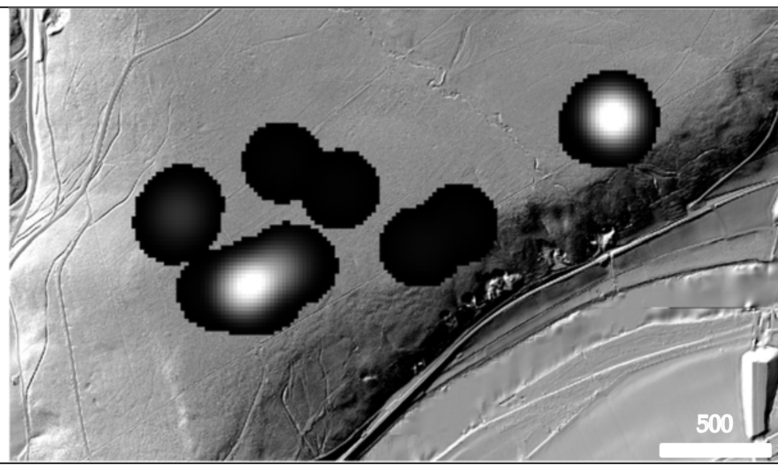
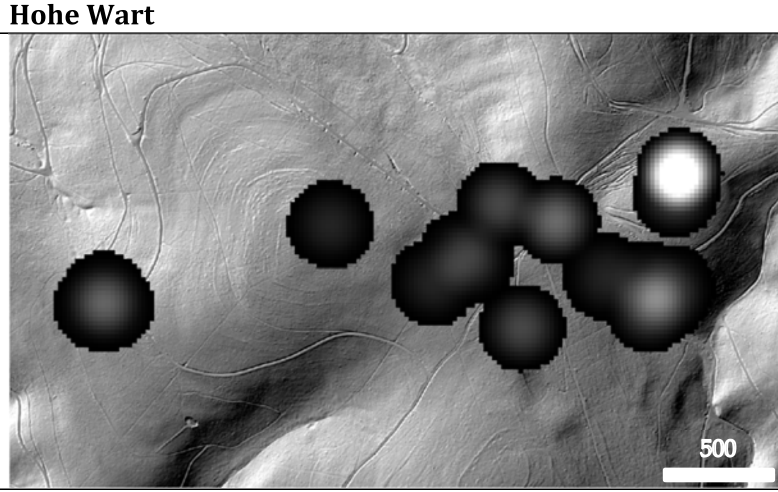
To quantitatively investigate the potential of qualitative visual detection, a focus group was tasked with detecting burial mounds within the nine sampling sites. The focus group consists of 16 archaeology students from different backgrounds, and with different experience. None of the students within the focus group are corrected during manual visual detection of archaeological monuments within the nine test sites, and can therefore be termed *"untrained data"*. Trained or untrained data is based on the notion of process of information extraction, compared to whether or not the control groups, algorithms or processes are encouraged or discouraged from adding new information and adapting along the way and any given task. It therefore does not refer to the experience or expert status of the participants involved, but rather the process by which the human participants where encouraged to extract information. Likewise, the algorithm is commanded to locate certain details within a given landscape. The algorithm is not trained to adapt to, increase or decrease, by variables, and is likewise coined untrained. However, all participants have an understanding of the physical extent of burial mounds and their presence in landscape. Similar the algorithm also has outline to locate based upon. The participants convert their own ideas and concepts of burial mounds towards visual detection of similar outline and pattern within the DEMs from the nine different sampling sites. Likewise, the algorithm is commanded to brute force match a given model of a standard burial mound to any given landscape, and find similar results in the two sets of input by given similarity criteria with output being extracted by confidence value.

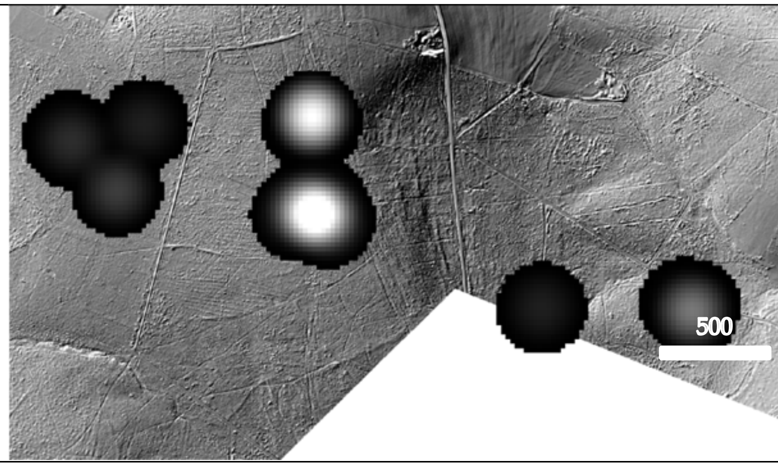
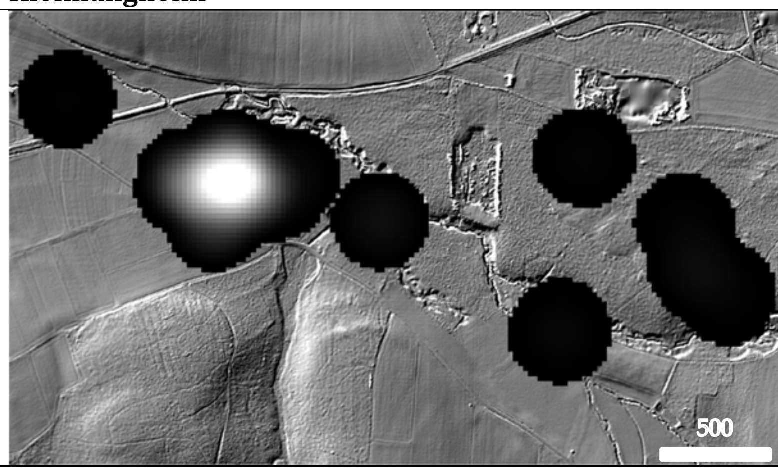
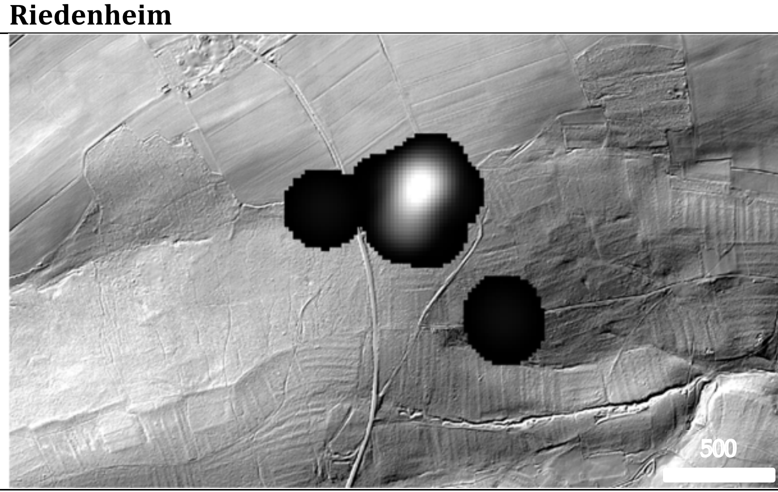
The results of the crowd-sourced visual detection can be seen in TABLE 13 and TABLE 14 below. As expexted, the test groups very well locating many of the burial mounds within the nine different test sites. The test group is not explained how many are possible to locate, or if even any. Even though they are confined to certain minimum and maximum expectations within given datasets, the results are very close to the ground truth verified burial mounds located from previous deskbased investigations and survey. Many of the areas detected naturally also contain some false positive detection. Similar false positives were detected by automated information extraction from the algorithm, and many areas have been surveyed as to deny or verify the possibility of burial mounds within the given landscape. Thus, true amount of burial mounds within a given dataset from the nine different sites, are almost certain. Naturally, almost completely destroyed and undetectable burial mounds with almost no curvature left in the terrain, are still possible to locate in most landscapes. From time of origin, all monuments of the landscape are impacted by many different factors, and many are completely submerged under present terrain in subsoil. The only possibility to truly know what is beneath the terrain is by the archaeological method. But even though complete verification will only come ones excavated, the landscape by vegetation and terrain still reveals many clues and patterns of our prehistoric past. Vegetation and terrain contain many clues to aid over interpretation and comprehension what is hidden beneath vegetation and terrain from both passive and active remotely sensed data by pattern recognition from humans and algorithms. For now, however, the investigation will focus on what is visible to detect by curvature in terrain, such as burial mounds by human cognition and computational commands.

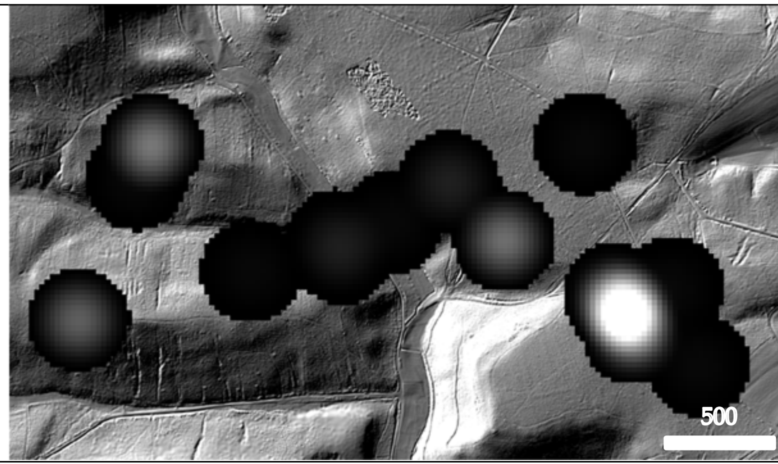
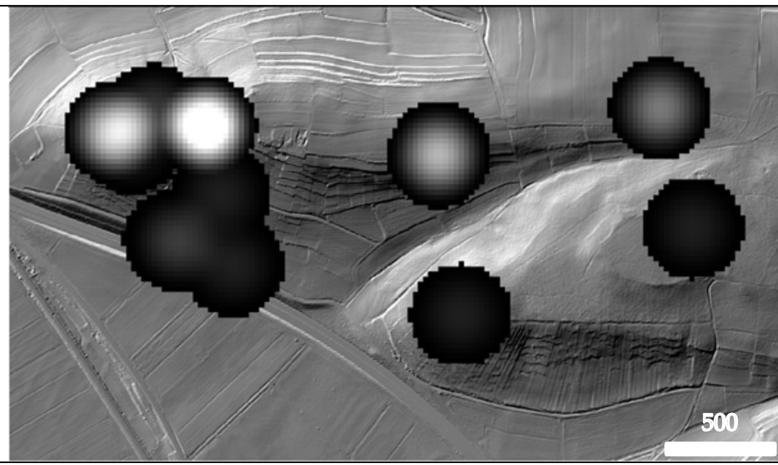
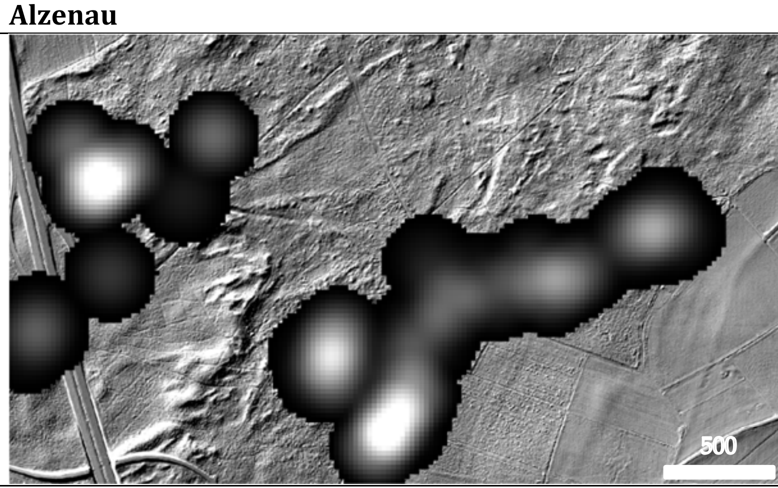
TABLE 13: BURIAL MOUNDS VERIFIED AT EACH SITE COMPARED TO CROWD-SOURCED DETECTION FROM THE FOCUS GROUP

No.	**SITE_name**	**Amount verified**	**Ave. crowd det.**
1	Stockstadt am Main	12	10
2	Triefenstein	25	15,06
3	Hohe Wart	1	5,53
4	Amorbach	1	5,26
5	Kleinlangheim	26	24,86
6	Riedenheim	11	9,2
7	Maroldsweisach	10	8,13
8	Stettfeld	2	2,4
9	Alzenau	20	9,46
	Total	**108**	**323**

TABLE 14: THE NINE SELECTED SITES WITH REPRESENTATION OF CROWD-SOURCED VISUAL DETECTION

NAME	**Stockstadt am Main**
Survey results for visual detection by kernel density. Radius 100, Cellsize: 10 Weight: count Gradient: black to white from less to more	
NAME	**Triefenstein**
Survey results for visual detection by kernel density. Radius 100, Cellsize: 10 Weight: count Gradient: black to white from less to more	
NAME	**Hohe Wart**
Survey results for visual detection by kernel density. Radius 100, Cellsize: 10 Weight: count Gradient: black to white from less to more	

NAME	**Amorbach**
Survey results for visual detection by kernel density. Radius 100, Cellsize: 10 Weight: count Gradient: black to white from less to more	
NAME	**Kleinlangheim**
Survey results for visual detection by kernel density. Radius 100, Cellsize: 10 Weight: count Gradient: black to white from less to more	
NAME	**Riedenheim**
Survey results for visual detection by kernel density. Radius 100, Cellsize: 10 Weight: count Gradient: black to white from less to more	

NAME	Maroldsweisach
Survey results for visual detection by kernel density. Radius 100, Cellsize: 10 Weight: count Gradient: black to white from less to more	
NAME	**Stettfeld**
Survey results for visual detection by kernel density. Radius 100, Cellsize: 10 Weight: count Gradient: black to white from less to more	
NAME	**Alzenau**
Survey results for visual detection by kernel density. Radius 100, Cellsize: 10 Weight: count Gradient: black to white from less to more	

The results of visual detection by the focus group is not simply interesting because of false or correct detection rates, but equally by the selection patterns and highlighted areas of interest. Within the nine sampling sites, there are 108 verified mounds based on initial visual detection and field survey testing, however, with the site of Alzenau very much an extreme site of uncertainties. The mean amount of detected burial mounds by the focus group are 89,9 burial mounds within all nine sampling sites. On average, the individual visual detection is very similar to the verified results. At sites with less burial mounds, the focus group generally detects more false positive burial mounds. At sites with a higher frequency of burial mounds, the focus group generally selects less than is actually present. The individual selection patterns can be seen and correlated between TABLE 14 and TABLE 15.

TABLE 15: SELECTION COUNT BY VISUAL DETECTION FROM INDIVIDUALS FROM THE FOCUS GROUP ON X-AXIS, SITE-ID BY SITE-NUMBER ON Y-AXIS

S.No	**Ver.**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**
1	12	15	13	5	9	10	7	11	14	7	8	9	9	9	4	12	8
2	25	16	18	15	13	18	20	14	16	15	14	12	12	7	12	16	8
3	1	6	50	1	2	4	2	1	4	4	2	1	2	2	2	0	0
4	1	9	30	2	3	1	4	5	12	3	1	1	1	3	2	1	1
5	26	19	25	26	19	30	24	32	30	29	19	18	19	16	22	20	25
6	11	7	17	10	7	9	9	10	9	11	6	6	7	6	9	7	8
7	10	10	10	8	6	8	8	8	9	6	7	7	9	2	13	6	5
8	2	5	0	4	2	0	2	2	2	3	1	1	6	2	5	0	1
9	20	30	40	6	8	27	10	0	0	1	0	0	2	1	14	0	3

What is also present in the correlation between the different tables, are the selection of several false positives. By the visualization of density selection in TABLE 14, it is evident that the areas that are continuously selected by the focus group are areas of interest containing burial mounds and burial mound clusters. Therefore, though some individuals of the focus group might make erroneous selection, the combination of the entire focus group makes for complete or almost complete coverage of true burial mounds within the nine sampling sites. The confidence value of selection relates to the areas of interest by a gradient from 0 to 1, from black to white. At each and every site, the maximum density selection always indicates an actual burial mound or burial mound cluster, indicating that crowd-sourced visual detection by an untrained group returns quantitative data useful for estimation and segmentation of landscape towards key areas of interest and improved information quality.

By closer inspection, it can also be seen how human cognition selects by macro patterns. Meaning, the human cognition used within the focus group is by contextual selection in linking to vicinity interpretation and relation. The individual burial mounds not clustered, is to some extent selected by the focus group from the nine sample sites. However, in the near vicinity of original selection the area surrounding is more meticulously investigated and more likely to embrace additional selections.

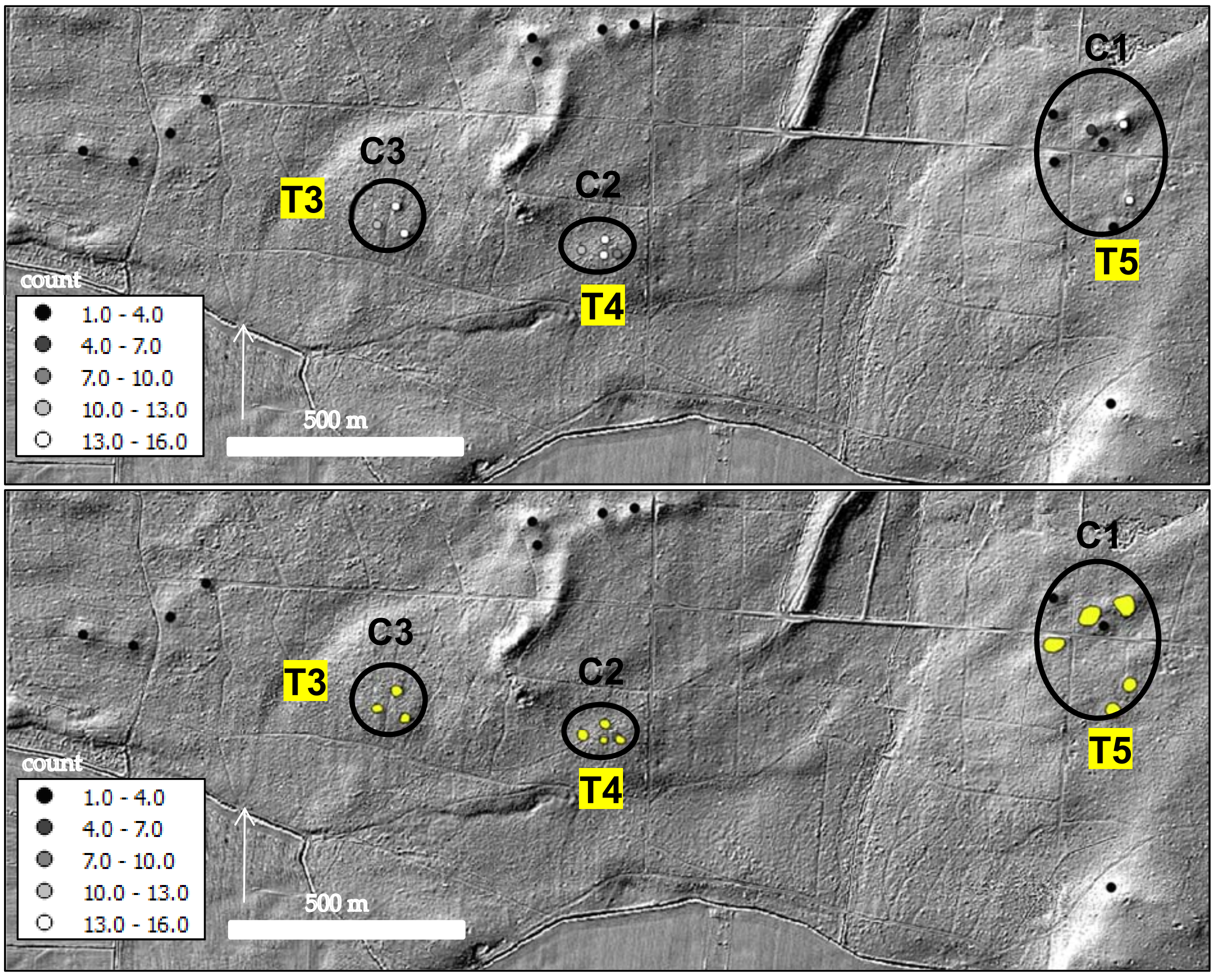


FIGURE 43: ABOVE: AREAS SELECTED BY THE FOCUS GROUP AS BURIAL MOUNDS BY COUNT AT THE SITE OF STOCKSTADT. C MARKS CLUSTER GROUP. T MARKS TRUE COUNT. BELOW: TRUE BURIAL MOUNDS MARKED AS YELLOW POLYGONS.

Within the three known clusters of burial mounds at the site of Stockstadt, all have the highest amount of selections across the focus group, but by different extents of exact detection (Figure 43). None the less, they contain the majority of selections, and as a result contain the greatest visual detection confidence of burial mounds. The outliers of false positive are by comparison much less prevalent across the selections of the focus group. From the site of Stockstadt, 10 false positives were selected, but with a complete detection of all true burial mound positives. The result is a false positive detection rate of 1.6 at the site of Stockstadt, considerably improving some state of the art detection rates by automated computational detection of 4 and 3.7 times as many false positives (Trier & Pilø 2012; Schneider et al. 2015). For the focus group, the number of false positive detections varies greatly from site to site by different individuals, with some sites having detection rates 50 times higher than true positives. This is true from the site of Hohewart, site no. 2, with a particular extreme detection rate by one test person. For visualization purposes, this necessitated removal from the kernel density visualization in Table 14 in order to be properly visualized. However, the overall detection rates of the entire focus group remained at 5.5 times as many false positive selections, despite the extreme outlier of one person. Removing this test person entirely from the case study of Hohewart, results in a false positive detection rate of 2.2, thus improving the result significantly. Similarly was the case study of Amorbach, site no. 4, with 30 times as many false positive selections by the same test person within the focus group. Likewise, this required removal from the kernel density representation in Table 14 in order not to skew the visualization. From Amorbach the average selection rate is 5.2 by all test persons from the focus group, but by removing the individual outlier this improves the detection rate to 3.2 times as many false as true selections. From all sites, the confidence of detections is indicated by the amount and pattern of selection. By the frequency of selection by the focus group at the site of Stockstadt, the confidence can be determined. Nine burial mounds from the site of Stockstadt are selected by such a high frequency that they contribute as very certain detections, whereas the remaining 14 irregularities selected by the focus group, represent more uncertain detection by rate of selection frequency (TABLE 16; FIGURE 44).

TABLE 16: DETECTION BY FOCUS GROUP GENERATING CONFIDENCE VALUE BY SELECTION. THE NINE MOST CONFIDENT SELECTIONS ARE REPRESENTED IN BOLD

sel_ID	sel_count	sel_ID	sel_count	sel_ID	sel_count
1	**16**	7	9	21	1
2	**16**	8	5	22	1
5	**15**	12	3	23	1
9	**15**	19	2	11	1
10	**15**	16	2	13	1
6	**14**	17	2	14	1
4	**12**	18	1	15	1
3	**11**	20	1		

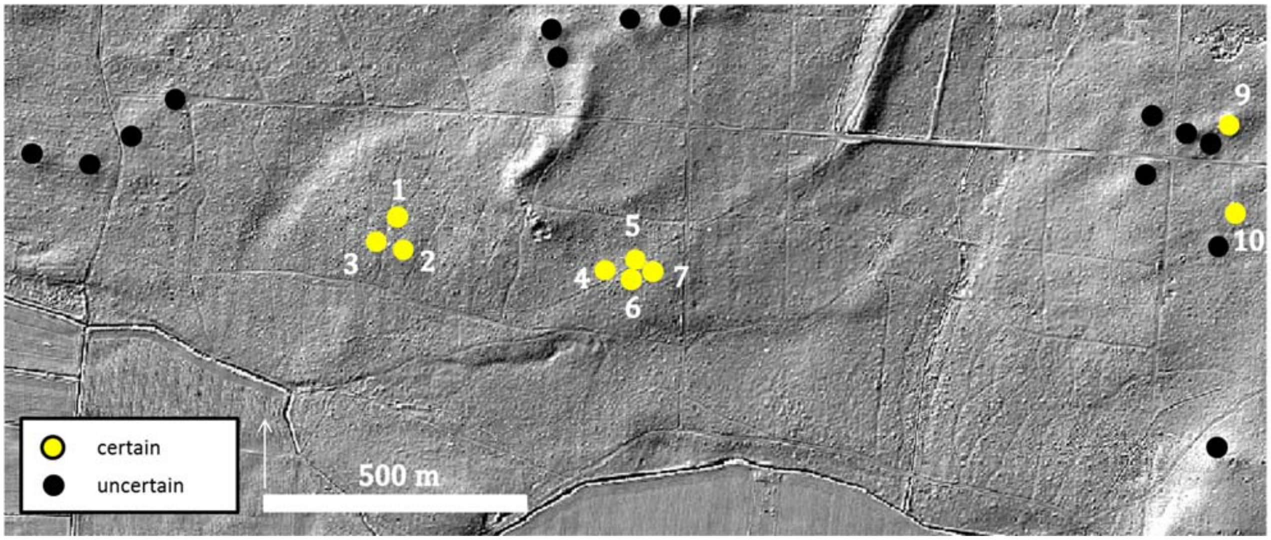


FIGURE 44: THE NINE MOST SELECTED BURIAL MOUNDS BY THE FOCUS GROUP. NUMBERING IS DETETERMINED BY SELECTION ID IN REFERENCE TO TABLE 16

The patterns from all sample sites are similar with the majority of selections being close to true burial mounds within the landscape, and continued selections in areas of interest in the vicinity of more confident selections. This, however, does not mean that all true burial mounds have high confidence values based on amount of selections, but rather that landscape is correctly segmented into areas of interest by visual detection. By removing outliers, the confidence is improved, and data exploration developed using less or simplified information. Similar to all Exploratory Data Analysis, *EDA*, the interpretation of patterns and removal of outliers, improves the quality of information (Tukey 1977.) The product is not simply constructed by the modelling of data, but rather what data is modelled. Naturally, such an approach requires equally tentative scrutiny as to not oversimplify, and create subjective patterns. The same can be said at each and every stage of data pre-processing, processing, and post-processing, because all steps require adaptation and testing before conclusion. The necessity required, is that any alteration can always be traced back to origin and original data, because any transformation is considered acceptable if steps of processing are traced and documented. Transforming data can improve the quality of information possible to extract, and thus benefit interpretation and conclusion. Therefore, any segmentation that improves possibilities of classification is beneficial to improve landscape interpretation for cultural heritage detection and management, whether that is by crowd-sourced data or by computational segmentation. For citizen science by crowd-sourced data, the benefits are present. It just requires that patterns generated are understood, and thus investigate structures and not outliers.

5.6 COMPUTATIONAL MOUND DETECTION BY TEMPLATES

Computational mound detection by templates is fundamentally brute-force matching towards given threshold of similarity. It offers a means of both segmenting and classifying landscape by output, and shows great potential for cultural heritage management and detection of archaeological monuments. Template matching is generally model driven by correlating entities with strong or weak features of comparison for filtering data. Dependent on scale and resolution of data and template, the detection can also be data driven, but is more commonly detection by filtering data by entities. Filtering data by templates offers possibilities of both segmentation and classification based on how data is processed. Template matching also delivers immediate detection output by given input, and can thus be an immediate classification if confidence of output is certain. However, that is rarely the case, and thus similar to most methods of landscape understanding, more compatible as a means of segmenting landscape. Within segmentation, as for crowd-sourced selection within remotely sensed data, classification can similarly be based on thresholds of confidence. Thresholds of confidence are then not constructed towards amount or percentage of detections, but rather on individual similarity between dual input entities. The fundamentals of output are therefore different, but with possibilities of similarity comparison between automatic extraction and manual visual detection. For comparison, the same nine sample sites have been used for automatic detection by entity filtering through model driven templates. The algorithms and code for filtering and detecting in the following case study are used and build in relation to the open-source library sharing of OpenCV, *Open Source Computer Vision* (Itseez 2015). OpenCV is the collection of many libraries for open programming functions, but specifically targeting computer vision and image analysis. The following code adaptations and build is based on the general-purpose programming language of Python. Template matching is structured on dual image inputs by source image(s) and template image(s) in order to find similarity between two individual images or catalogues. The threshold of similarity determines confidence of output, and output can then be given similarity value to define certainty of classification. However, archaeological data is often imperfect and heterogeneous without strong edges or feature indicators, resulting in similarity calculation accepting deviance between template and source image.

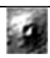
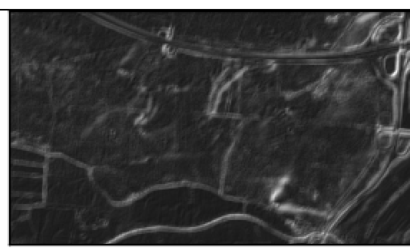
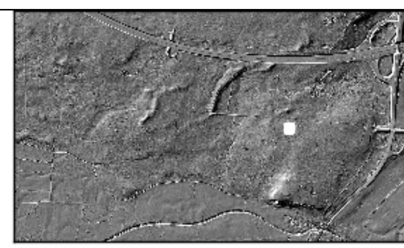
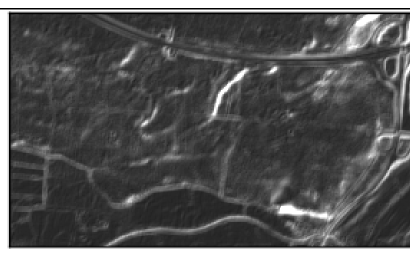
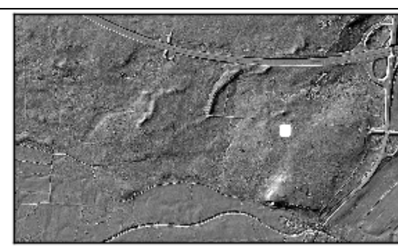
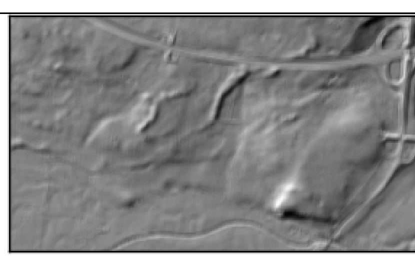
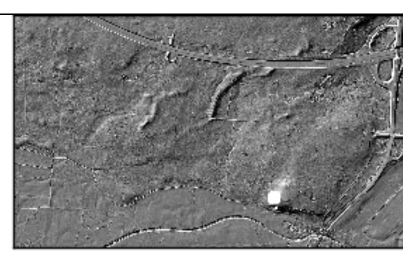
The similarity coefficient is based on calculating distance to similarity or dissimilarity, and template matching is commonly run by simple brute-force matching. Brute-force matching slides or moves descriptor values from template to source image across the entire raster, and thus calculates as a model driven approach between individual target-XY to source-XY position by output value of dissimilarity or similarity between 0 to 1, or minimum to maximum. The output is the sum of absolute differences in result, defined by **R**(x,y) (see also

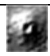
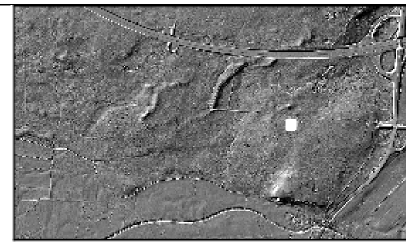
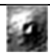
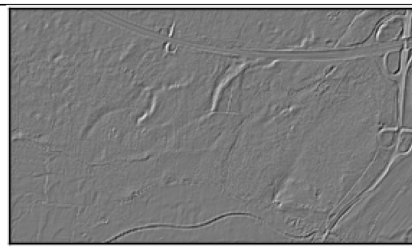
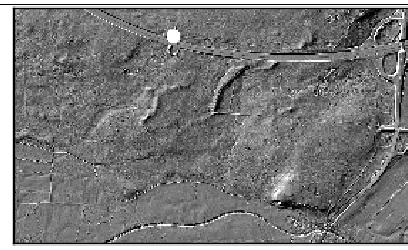
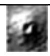
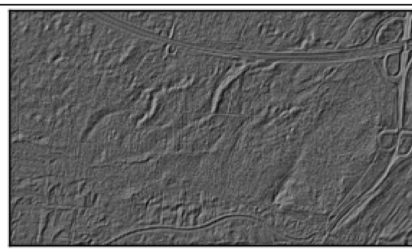
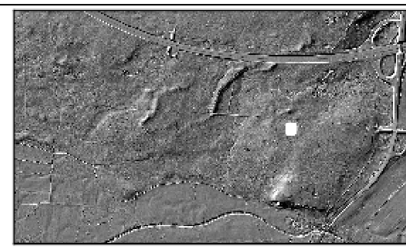
The correlation coefficient function also has the greatest possibility of tracking changes in detection by having a constant to relate quantitative values by, and thus simplifying threshold to more applicable values. This makes for better qualitative assessment of impact on changes in threshold. The coefficient function is displayed in EQUATION 4 below.

EQUATION 4, p. 147). Thus **R** is the result between compared template and compared data based on similarity and dissimilarity of given XY-area of comparison. Only areas of given rules and parameters, e.g. threshold value or similarity value of minimum 0.5 results in detection. Overlap is reduced by selection through best fit, meaning the most similar detection is choosen as final extraction target.

The correlation coefficient function also has the greatest possibility of tracking changes in detection by having a constant to relate quantitative values by, and thus simplifying threshold to more applicable values. This makes for better qualitative assessment of impact on changes in threshold. The coefficient function is displayed in EQUATION 4 below. The matching function is chosen by evaluating matching results based on six different equations by same template to same source image from the site of Stockstadt (TABLE 17).

TABLE 17: EVALUATING DIFFERENT MATCHING FUNCTIONS

Template	**Match. Pro.**	**Matching calculation**	**Matching result 1:1**
	SQDIFF		
	SQDIFF_N		
	CCORR		

	CCORR_N		
	COEFF		
	COEFF_N		

Based on initial results in TABLE 17, the pattern representation shows normalizing data makes for correct detection at every matching procedure. Normalizing data represents standardizing data input variation to a threshold of 0 to 1. This improves or minimizes light variation within individual input, as well as correcting and standardizing input between template and source image. In the above matching functions, the filter is set to locate maximum similarity, and thus locates a singular detection by maximum similarity. The correlation and coefficient equation both detect false positives, but all normalized equations make correct detection based on same given template input.

The landscape at the site of Stockstadt does consist of some changes in elevation, and therefore best similarity match also consist of false positives almost impossible to avoid. This was also seen by the crowd-sourced detection of burial mounds within the landscape. However, the minimum and maximum elevation is not extreme, therefore normalizing the raster DTMs at the site of Stockstadt does not involve major extremes of elevational change necessary to incorporate, but some modern structures disturb the elevational differences in the landscape (FIGURE 45). If source input and template is very dissimilar by visual differences, such as elevational differences, this can impact the automated detection success. Therefore, source and template needs some correlation to be effective, and target specific templates to landscape are better for different landscapes. This can be somewhat helped by normalizing data, by improving correlation between source and template.

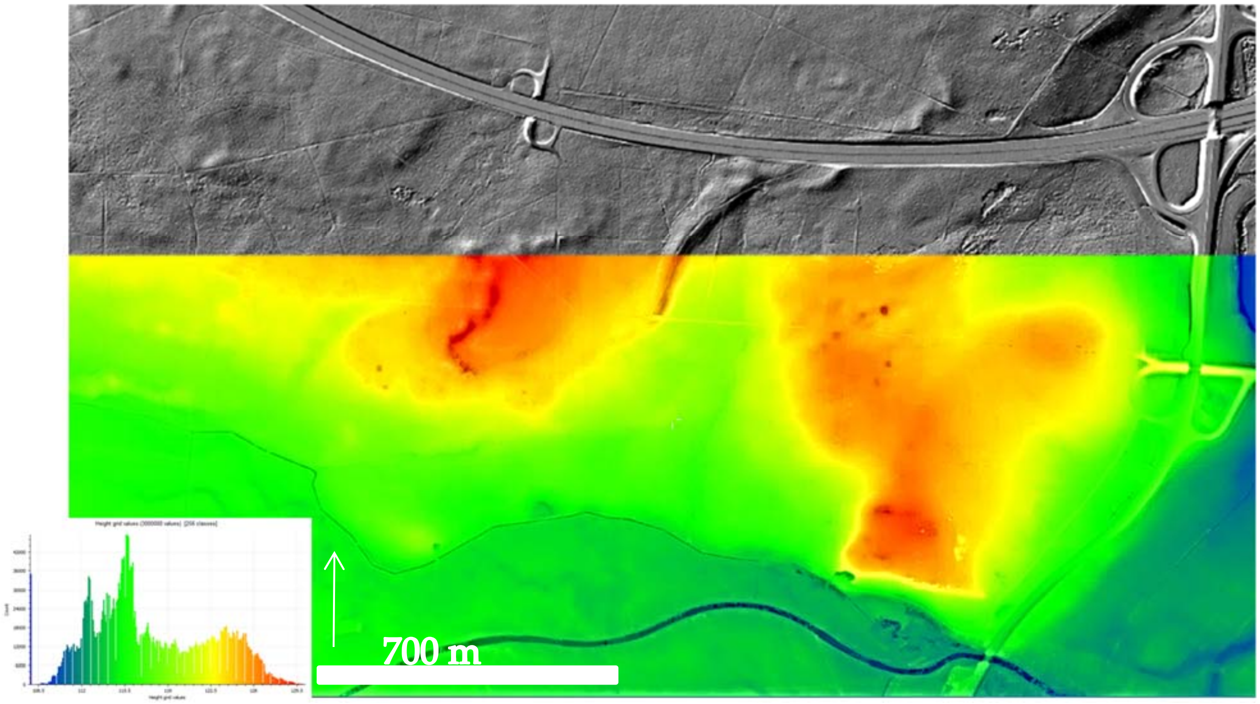
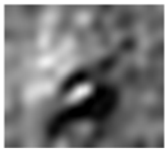
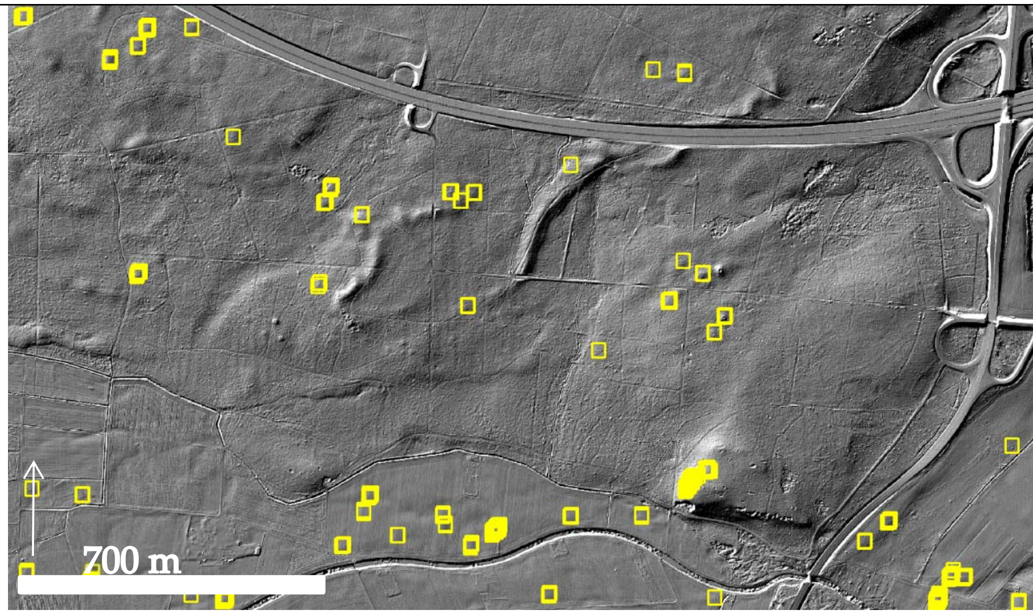
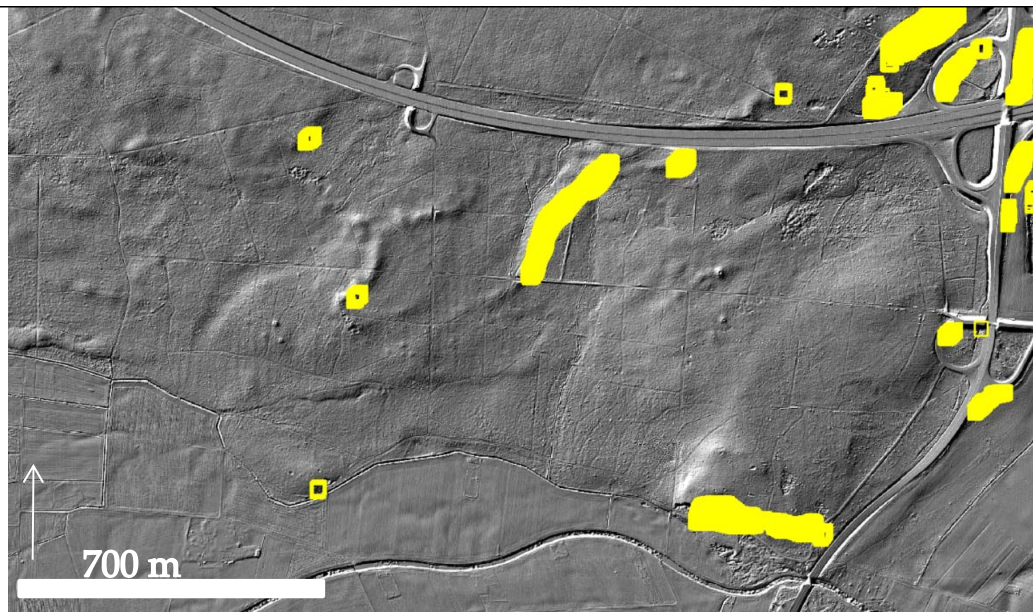
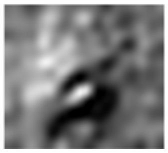
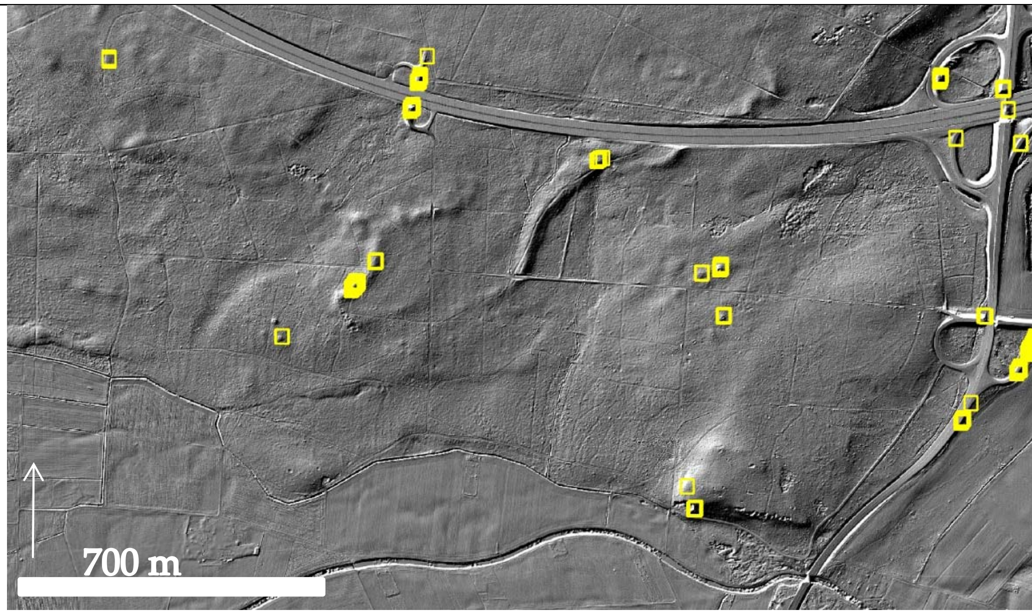


FIGURE 45: ELEVATIONAL DIFFERENCES AT THE SITE OF STOCKSTADT. HISTOGRAM SHOWS ELEVATIONAL DISTRIBUTION

For automated detection, when the threshold filter of similarity is lowered, the detection changes and shows that some equations are more applicable than others. The following examples of this will only show the equations that normalize data as they have proven more proficient. Normalizing data represented better results in detection by lesser similarity than represented in the non-normalized data. The threshold of similarity was lowered towards finding best match, resulting in threshold value changing between different equations. Best match of true detections was then pursued towards improvement of automated detections. The best match of the three equations was by the normalised correlation coefficient, COEFF_N (TABLE 18).

TABLE 18: THE THREE EQUATIONS AND THEIR IMPACT ON DETECTION: NORMALIZED CORRELATION, NORMALIZED SQUARED DIFFERENCE, AND NORMALIZED COEFFIECIENT

CCORR_N Best match Threshold val: 0,935 Template: 	
SQDIFF_N Best match Threshold val: 0.9 Template: 	

COEFF_N Best match Threshold val: 0.5 Template: 	

The correlation coefficient function also has the greatest possibility of tracking changes in detection by having a constant to relate quantitative values by, and thus simplifying threshold to more applicable values. This makes for better qualitative assessment of impact on changes in threshold. The coefficient function is displayed in EQUATION 4 below.

EQUATION 4: FUNCTION EQUATION FOR MATCHING SIMILARITY BY CORRELATION COEFFICIENCE

(FROM ITSEEZ 2015)

I DENOTES IMAGE, T TEMPLATE, R RESULT

$$R(x,y) = \frac{\sum_{x',y'} (T'(x',y') \cdot I'(x+x',y+y'))}{\sqrt{\sum_{x',y'} T'(x',y')^2 \cdot \sum_{x',y'} I'(x+x',y+y')^2}}$$

The matching equation applied to the nine sample sites, slides template through source image and compares overlapping patches. The function compares sums to maximum similarity between template and source image. Sum is done over source patch by : x' = 0…w – 1,y' = 0… 1. This is implemented as template matching in the programming language of Python, and used as an execution of two data inputs of source and template. The code is represented below with the matching function applied in TABLE 19 and represented at all the nine sampling sites in TABLE 20.

TABLE 19: THE APPLIED PYTHON SCRIPT FOR OPENCV TEMPLATE MATCHING

```
1
2    # import modules
3    import cv2
4    import numpy as np
5    from matplotlib import pyplot as plt
6
7    # source image to display
8    img_rgb = cv2.imread('inp4286_5541.tif')
9    img_gray = cv2.cvtColor(img_rgb, cv2.COLOR_BGR2GRAY)
10
11   # template image to display
12   template = cv2.imread('temp.png',0)
13   w, h = template.shape[::-1]
14
15   # Matching and Normalize
16   res = cv2.matchTemplate(img_gray,template,cv2.TM_CCOEFF_NORMED)
17
18   # set confidence value by threshold of similarity.
19   threshold_value = 0.5
20   loc = np.where( res >= threshold_value)
21
22   # Draw on output image
23   for pt in zip(*loc[::-1]):
24       cv2.rectangle(img_rgb, pt, (pt[0] + w, pt[1] + h), (0,255,255), 2)
25
26   # Display on output image
27   cv2.imwrite('outp4286_5541.tif',img_rgb)
28
```

The script runs import of the OpenCV library, together with numpy and matplotlib. The script handles color adaptation and correction to greyscale, in case of application of other remotely sensed data, i.e. aerial imagery. The matching is done by sliding iterations by patch over source image via template to defined threshold value between 0 to 1. The output is vectorized squares on source image, directly capable of import to any GIS of preference afterwards. The output does not have extent defined, but since source image is georeferenced, the coordinate system can be transferred to new output from original source image extent. The above script runs from the second line merely by a choice of aesthetics of visualization and readability in present display. Equally, it runs an extra line below the entire script, but both are redundant. The input can consist of all raster, and by normalizing data source image and template can be transferred from different context. However, template needs to be of similar scale, since template slides over as patch calculation. Individual size of curvature is possible to be scaled based on given threshold value, meaning that burial mound size can alter. The above example in TABLE 18, are similarity calculations only based on one extracted template within the site, but gives a first rough estimate of matching functions applicable.

Using the information gained from first initial template matching, there are certain details that can be used to improve detection. Many of the detections are based on modern construction, such as ditches near roadways having similar curvature or details similar. Many of the false positives can be directly excluded by a buffer excluding details within modern building activity, making the landscape much more comprehensible to interpret (FIGURE 46).

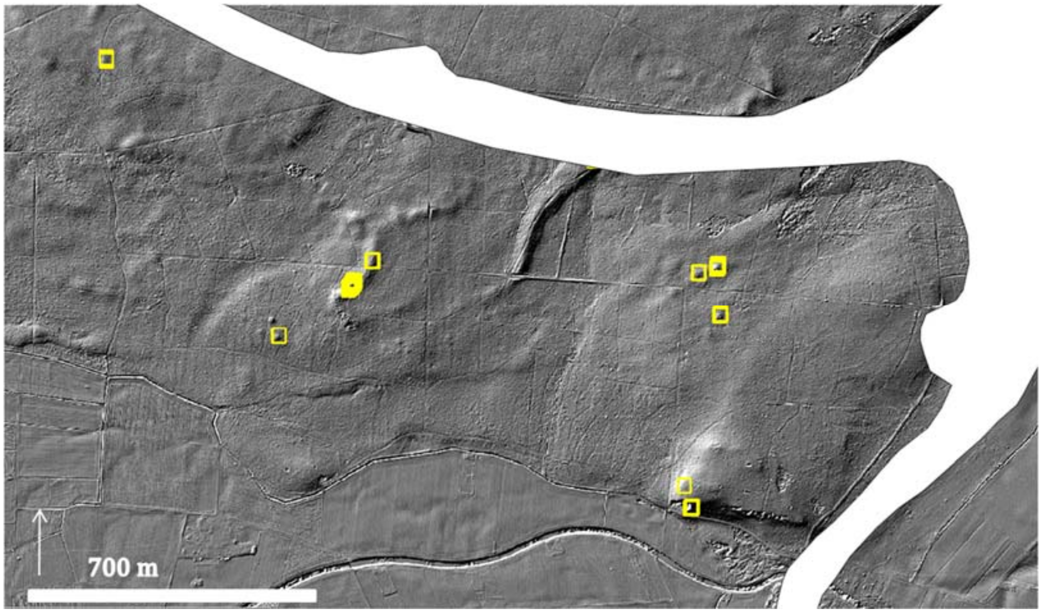


FIGURE 46: REMOVING MODERN CONSTRUCTION BY FILTERING OUT MAJOR ROADS

However, the result of detections made by the template filter, visualize that many of the true burial mounds are not detected, and many false positives detected instead (FIGURE 47).

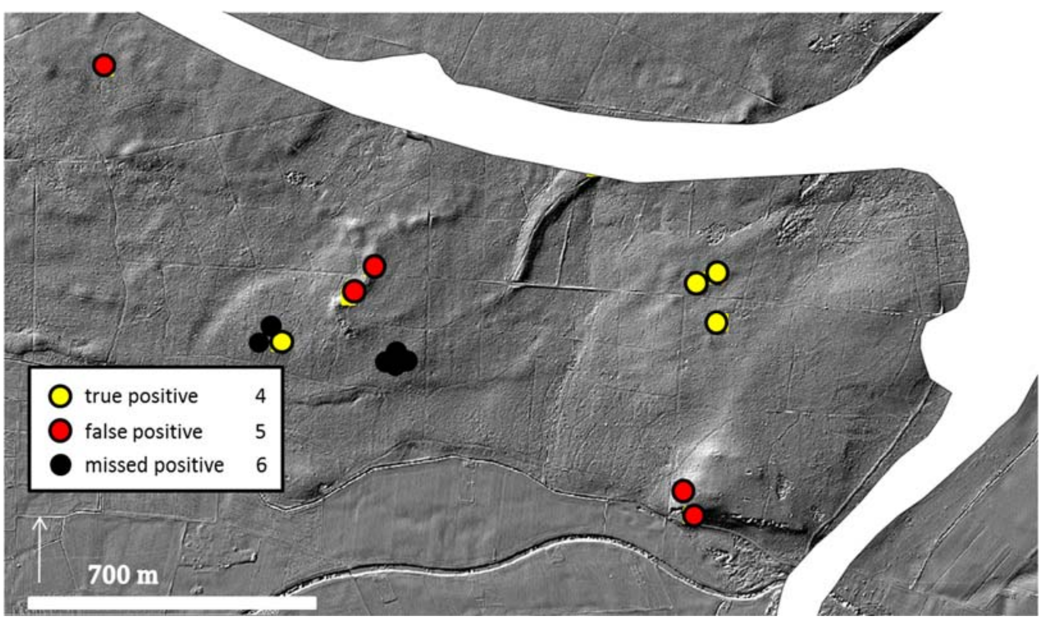
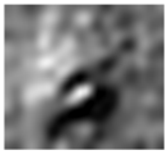
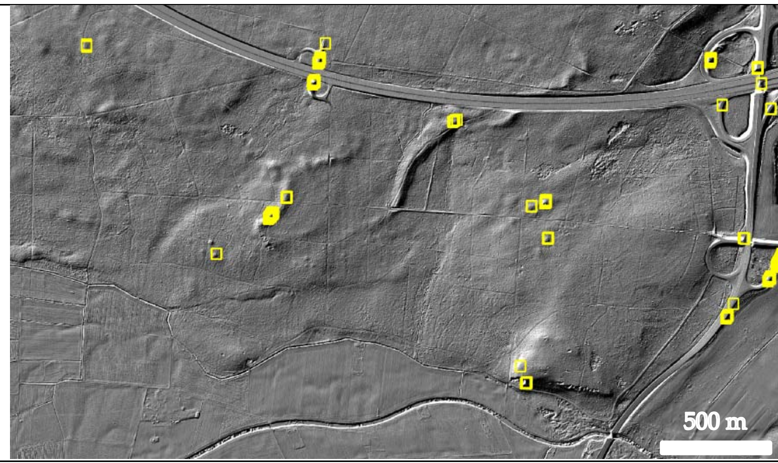
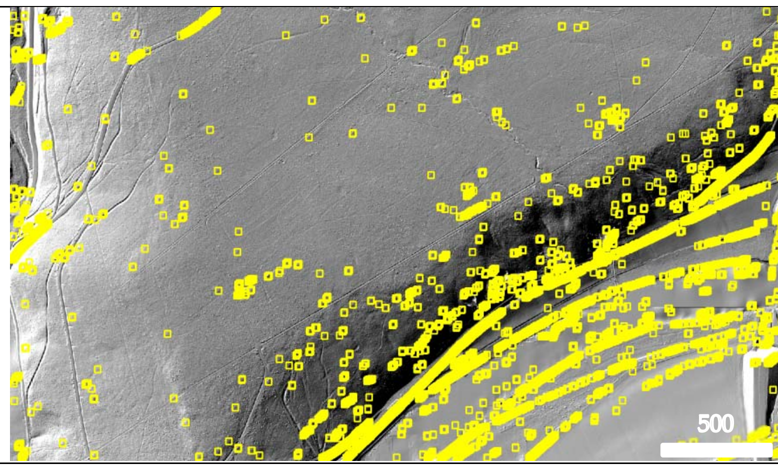
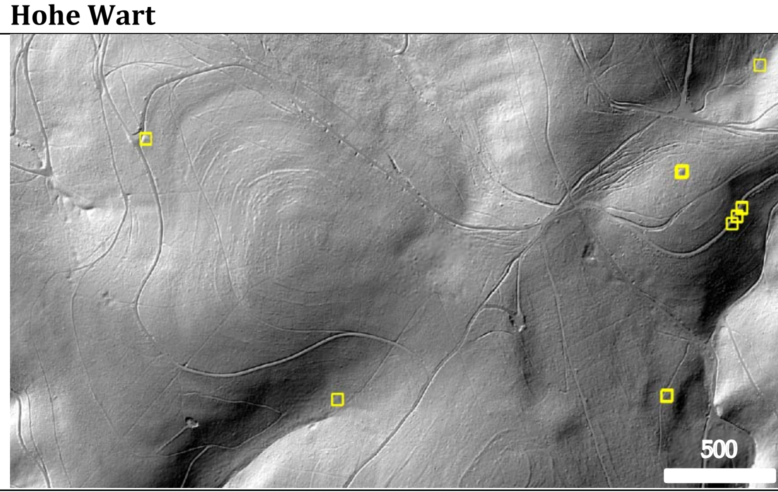
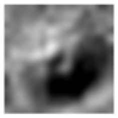
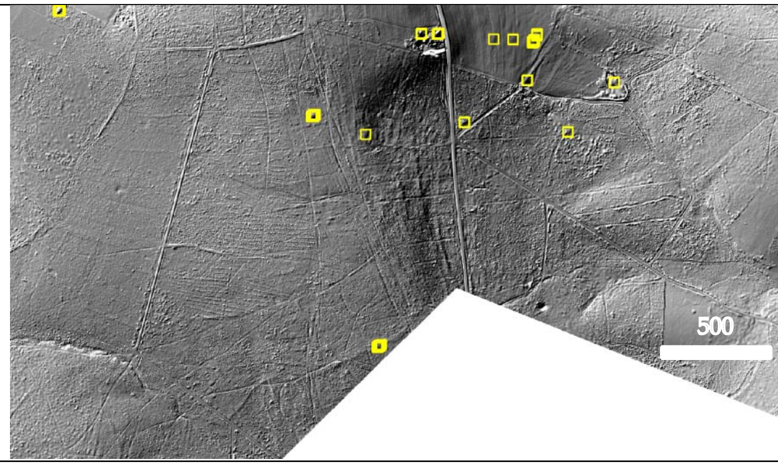
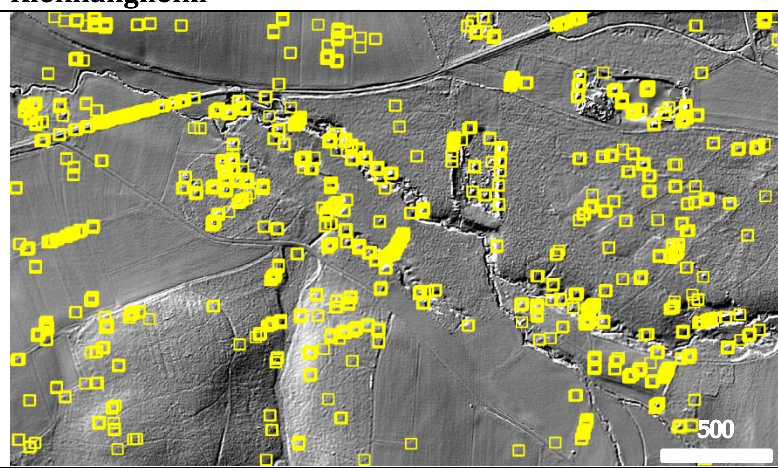
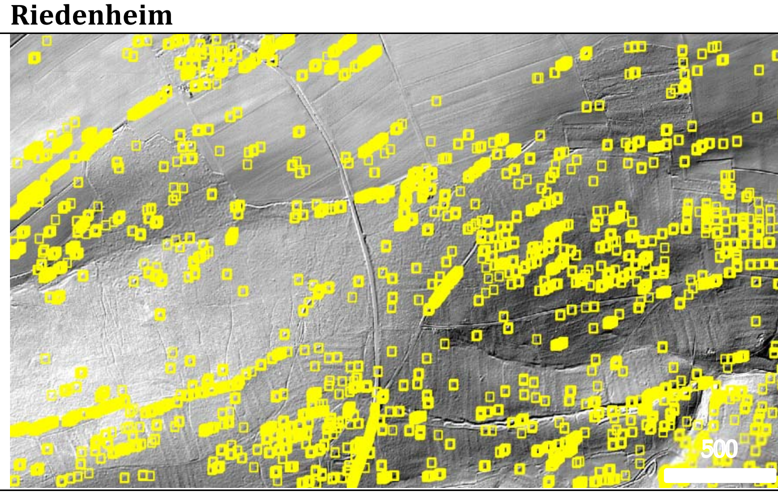


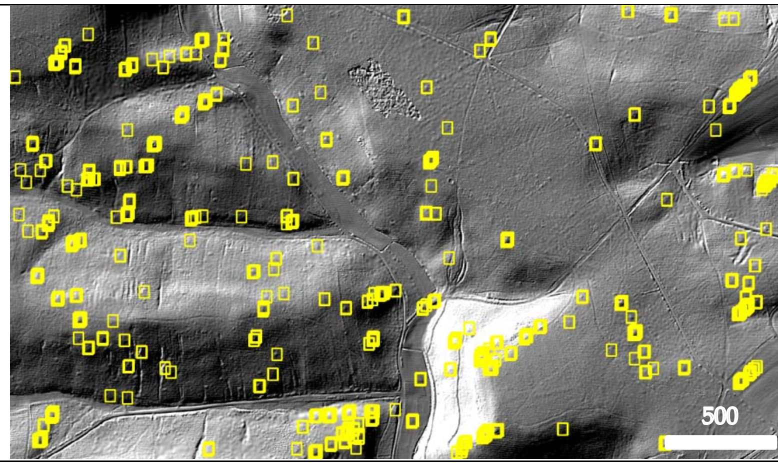
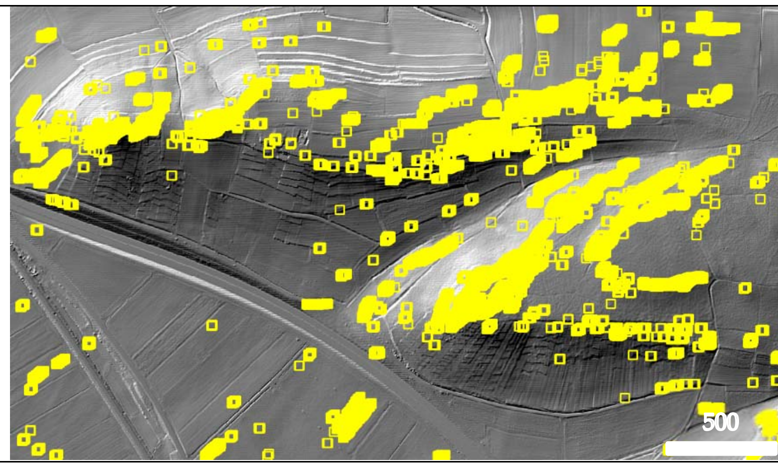
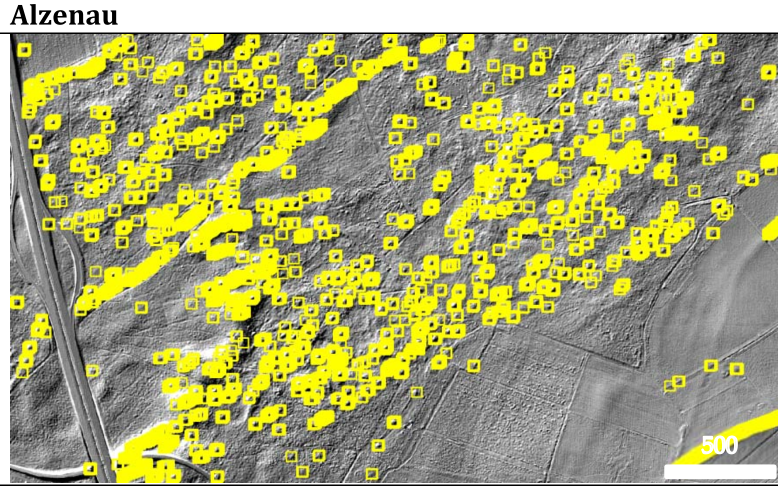
FIGURE 47: TRUE, FALSE, AND MISSED DETECTION BY INITIAL TEMPLATE FILTER

The initial detection resulted in 1.25 times as many false positives, but with 1.5 times as many missed true burial mounds. This ratio can be altered by changing threshold of similarity extraction. By increased similarity, more false positives are detected. With a lower threshold value, less true burial mounds are detected. Different threshold values have been applied, but a 50 % similarity to given template gave decent results, without missing to many important details of similarity in landscape. With a 50 % likeness of a threshold of value of 0.5, details of human manipulation, such as looters pits and other major destruction of original outline, is also possible for the algorithm to overlook to find burial mounds similar to the given template for matching. Different templates were tried, but will always result in similar exclusion of data if calculated output is very unique compared to input. Therefore, it is better to set a value where size and shape can differ to a large extent compared to template input. The confidence value of the threshold is set at 0.5, and is applied to all case study sites to further investigate all nine sampling sites to make a comparative between automatic information extraction and crowd-sourced information extraction of burial mounds. By information extraction through geometry and templates, there is an immediate classification of shape in the landscape; the problem simply becomes a matter of confidence regarding classification certainty. The confidence of detection is naturally of importance, but initial interesting aspects are what impact simple geometry detection across different context reveals by the pattern of detection. Initial simple geometry detection is applied in TABLE 20 by templates from site of investigation to reveal initial patterns of computational detection.

TABLE 20: TEMPLATE MATCHING BY SIMILARITY THRESHOLD OF 0.5

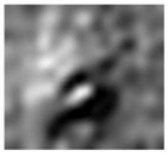
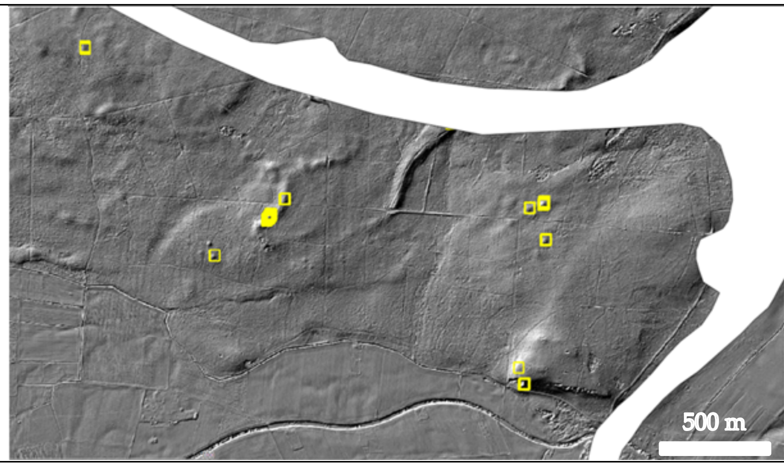
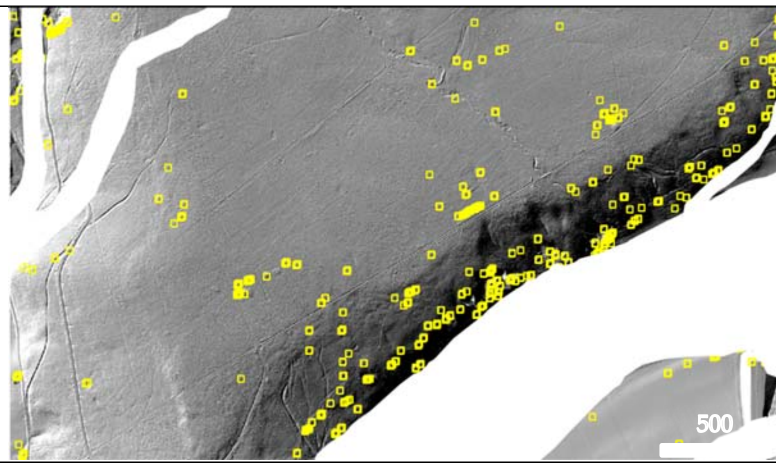
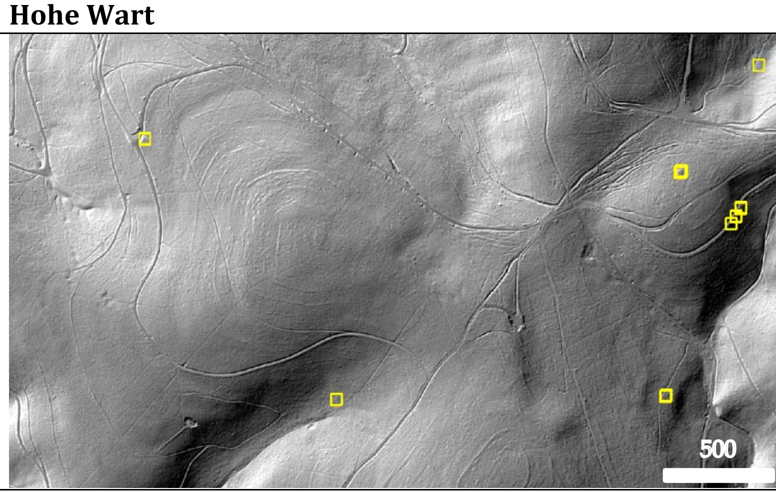
NAME	**Stockstadt am Main**
COEFF_N Threshold val: 0.5 Template: 	
NAME	**Triefenstein**
COEFF_N Threshold val: 0.5 Template: 	
NAME	**Hohe Wart**
COEFF_N Threshold val: 0.5 Template: 	

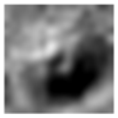
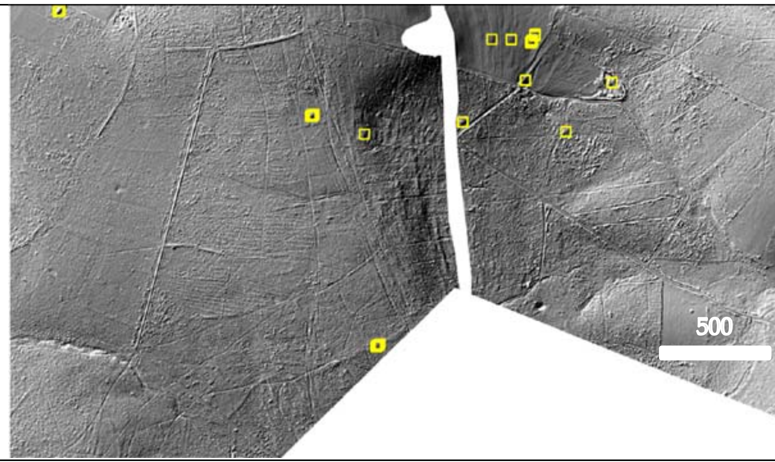
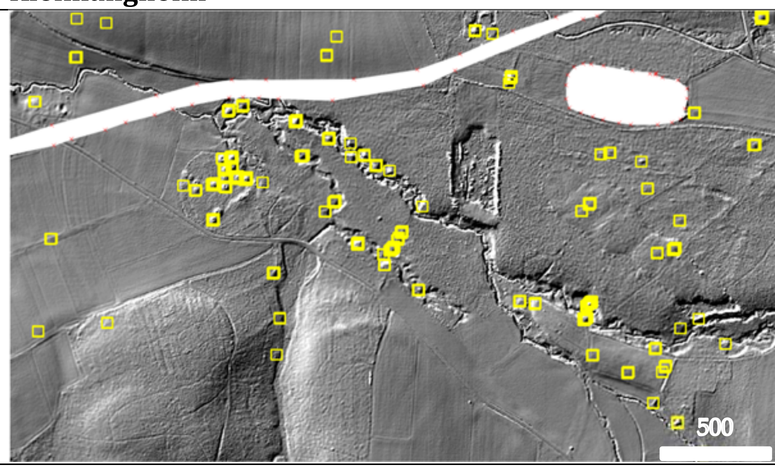
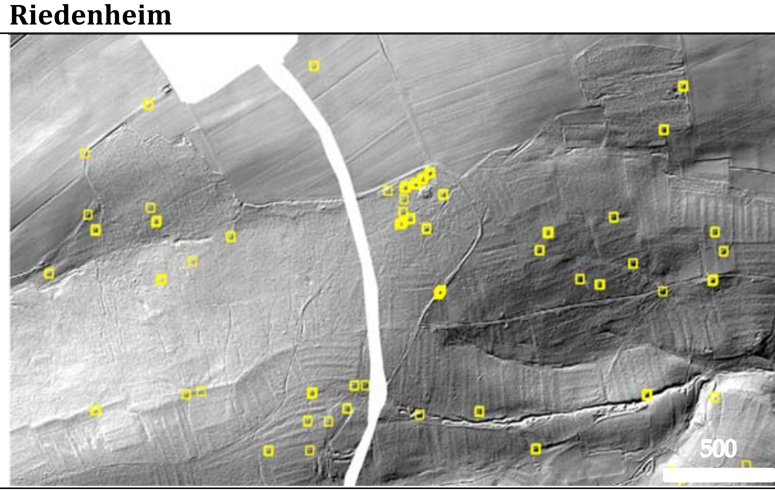
NAME	**Amorbach**
COEFF_N Threshold val: 0.5 Template: 	
NAME	**Kleinlangheim**
COEFF_N Threshold val: 0.5 Template: 	
NAME	**Riedenheim**
COEFF_N Threshold val: 0.5 Template: 	

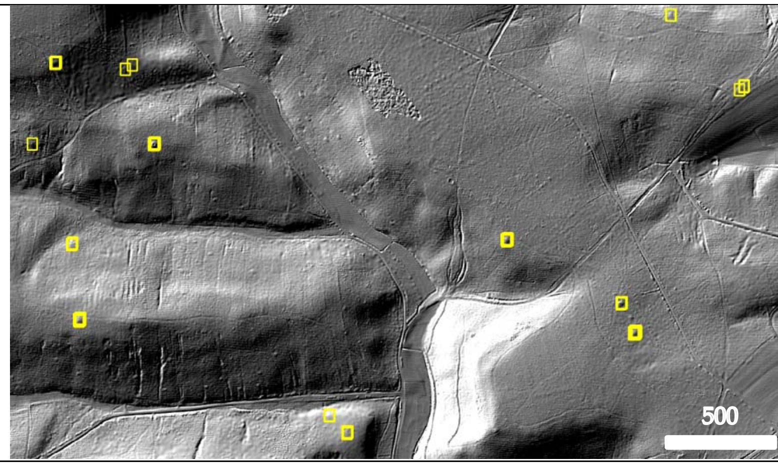
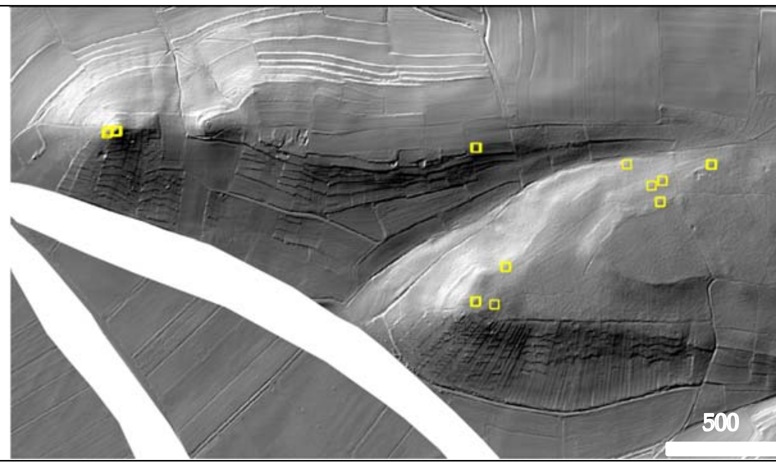
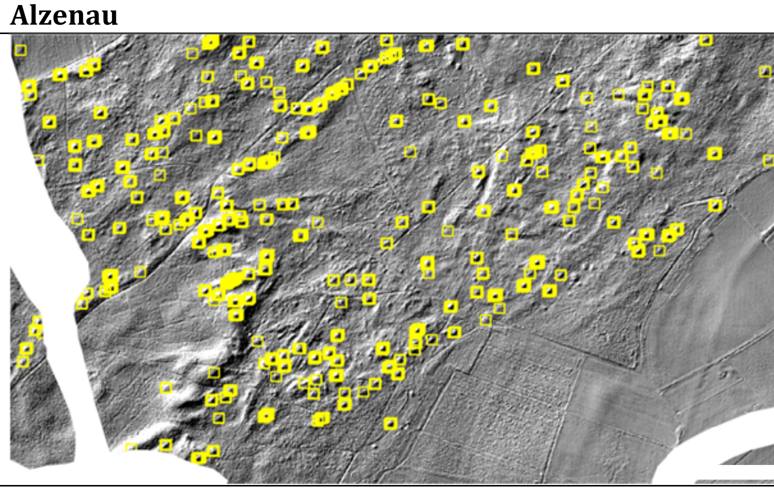
NAME	**Maroldsweisach**
COEFF_N Threshold val: 0.5 Template: 	
NAME	**Stettfeld**
COEFF_N Threshold val: 0.5 Template: 	
NAME	**Alzenau**
COEFF_N Threshold val: 0.5 Template: 	

The detection result in TABLE 20 is of very different quality by true and false positives from different context of landscape, but all follow the same steps of information extraction with a threshold similarity between source image and template being set at 0.5. The pattern of detection is scattered. A scattered pattern is to be expected since the selection process is by micro perspectives of individual characteristics within a template patch. Therefore, the pattern of detection is non-contextual. Any clustering or ordered pattern by template matching is objective detection by similarity of input, and not influenced by other features in the vicinity. The classification and interpretation of detection naturally then becomes subjective based on rules given to classify by, or background of interpretation. The rate of true and false positives is at some sites extremely skewed by similar curvature in the landscape, especially as a result of modern construction blurring the filtering possibilities. Therefore, it is, as before, necessary to remove and exclude detection within certain areas of modern construction by a buffer to extract more purposeful information. Naturally, this can also result in erroneous exclusion of features of interest within near vicinity of modern construction. In the near vicinity of modern constructions, the presence of recent artificial mounds and curvatures is too excessive to be filtered, but deceives both human visual detection as well as computational automatic detection. Therefore, it is necessary to exclude these areas by a buffer as presented in Figure 47 around major roadways. All modern construction, such as minor roadways, cannot be excluded, since it would remove too many details in the landscape. Therefore, the buffer will only be extended around major structures of modern construction. To improve rate of detection by template matching, the threshold value applied does not deliver equal good results across the different contexts of landscape. As a consequence, best match needs to be investigated by changing given similarity threshold at the nine different sampling sites. The similarity threshold can easily be adjusted to increase degree of similarity necessary for detection between source image and template to change and improve outcome. However, initial similarity calculation was set at the same threshold value to have comparable output. In order to improve, the following automated detection in TABLE 21, was designed towards finding best threshold match to given context, as well as buffer exclusion surrounding major parts of modern construction. The representation of script function in TABLE 21 by changing threshold values clearly shows necessary adaptation to different context of landscape by the amount of curvature represented.

TABLE 21: TEMPLATE MATCHING BY BEST THRESHOLD MATCH AND BUFFER-ZONES

NAME	**Stockstadt am Main**
COEFF_N Threshold val: 0.5 Template: 	
NAME	**Triefenstein**
COEFF_N Threshold val: 0.55 Template: 	
NAME	**Hohe Wart**
COEFF_N Threshold val: 0.5 Template: 	

NAME	**Amorbach**
COEFF_N Threshold val: 0.5 Template: 	
NAME	**Kleinlangheim**
COEFF_N Threshold val: 0.6 Template: 	
NAME	**Riedenheim**
COEFF_N Threshold val: 0.65 Template: 	

NAME	**Maroldsweisach**
COEFF_N Threshold val: 0.6 Template: 	
NAME	**Stettfeld**
COEFF_N Threshold val: 0.87 Template: 	
NAME	**Alzenau**
COEFF_N Threshold val: 0.6 Template: 	

The rate of detection by best match is producing many false positives, as is presented in TABLE 22.

TABLE 22: AMOUT OF AUTOMATICLY DETECTED BY TEMPLATE MATCHING

No.	SITE_name	Amount verified	Amount auto. det.	ratio false pos.	missed BM in area
1	Stockstadt am Main	12	9	0	2
2	Triefenstein	25	202	8	1
3	Hohe Wart	1	8	8	0
4	Amorbach	1	12	12	0
5	Kleinlangheim	26	69	2	0
6	Riedenheim	11	54	4	0
7	Maroldsweisach	10	15	1	1
8	Stettfeld	2	11	5	1
9	Alzenau	20	232	11	0

The extreme amount of false positives is a construct of amount of curvature in the landscape, often easily discernible by human cognition as non-burial mounds. The automated micro pattern detection therefore necessitates expert rejection and verification. However, all curvatures of similarity are selected, meaning that this is a construct for thorough remote survey of data for overview of geometry and curvature of interest. A majority of verified burial mounds are also detected, but with flat or destroyed burial mounds missed by automated detection of simple shapes through template matching. The overall pattern of all extracted information is focused on the individual information of curvature in the landscape. Occlusion and rejection of many false positives are easily attainable by expert investigation, but also by filtering out areas containing obvious modern impact on rate of detection. The pattern of detection also follows some tendencies and trends of interest of curvature and curvature clusters in the landscape not detected by the focus group and crowd-sourced data. There are therefore some obvious differences in interpretation of landscape that makes for different segmentation and classification of landscape, also impacting finale quality of information extracted. Naturally, the threshold values used for similarity detection can be reduced or increased to either increase or decrease details detected. The thresholds selected, though, appear to fit the different sampling sites by encompassing best results of detecting true positives while not excluding considerable amounts of detail. However, the truly interesting aspects of template matching, is the pattern of detection, and how this pattern of detection is comparable to crowd-sourced data. While both methods of detecting and segmenting landscape do not directly compare, we will see in the following how the individual patterns reveal improved quality of information extraction.

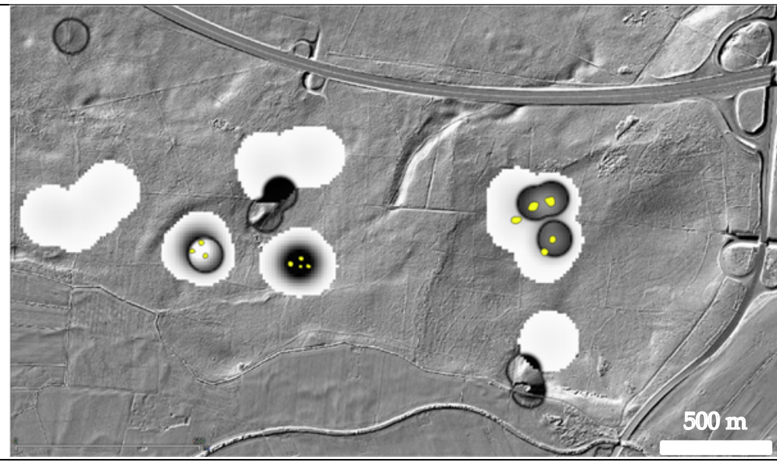
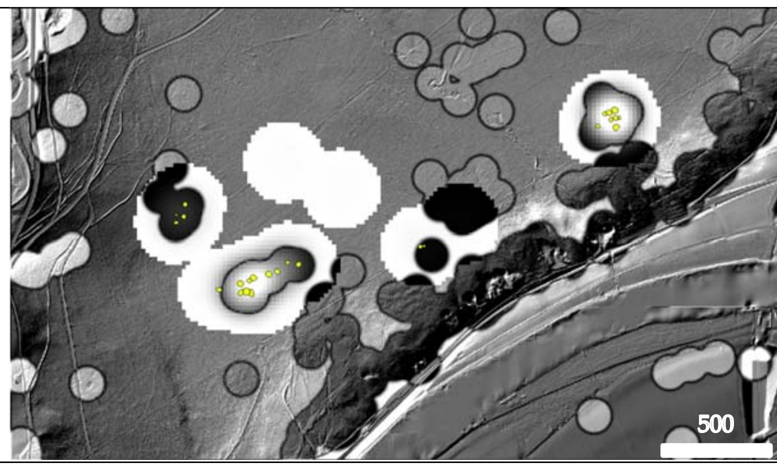
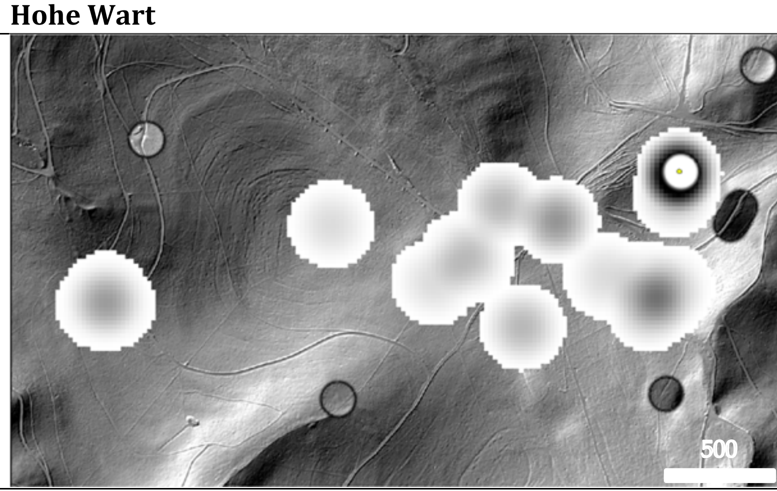
5.7 COMPARISON BETWEEN CROWD-SOURCED DATA AND TEMPLATE MATCHING

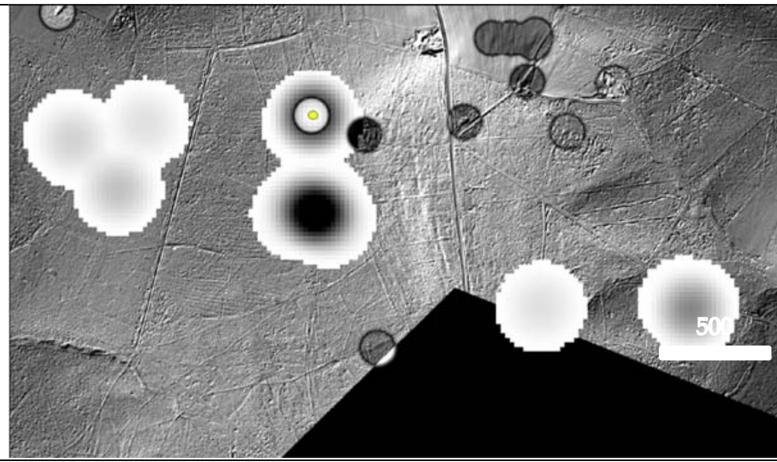
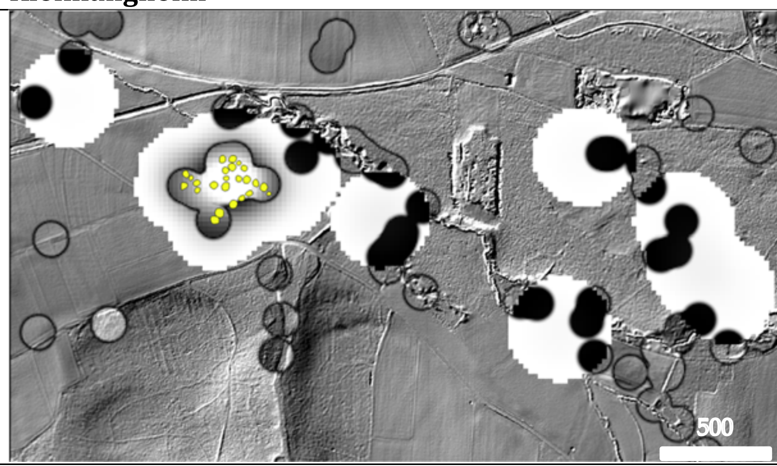
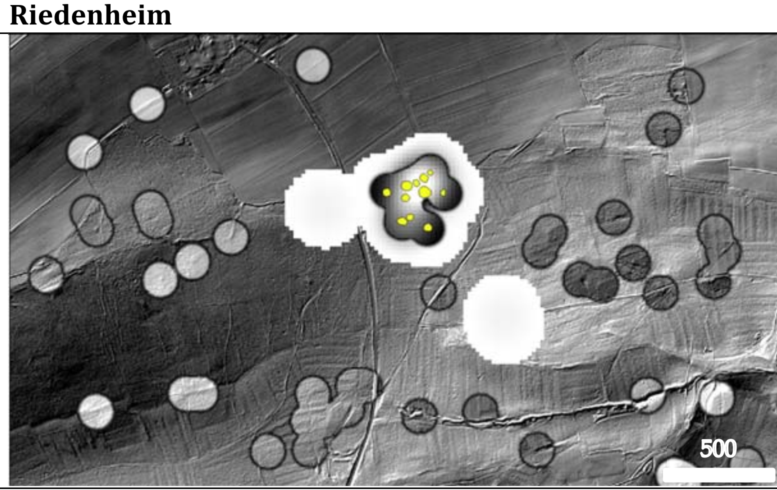
Data from crowd-sourcing information extraction reveals segmentation patterns capable of improving detection for large-scale cultural heritage management. Equally, the patterns of simple geometry of template matching by open-source principles, reveals segmentation patterns capable of improving detection for large-scale cultural heritage management. The data extracted from template matching is visualized as segmentation in TABLE 23 together with the crowd-sourced data extracted by the focus group. The product is segmented parts of landscape, revealing key areas of interest for understanding amount and presence of burial mounds within the nine different sampling sites.

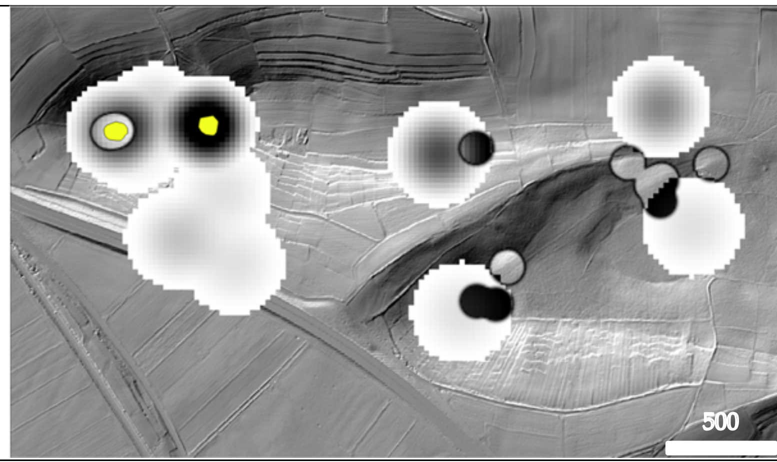
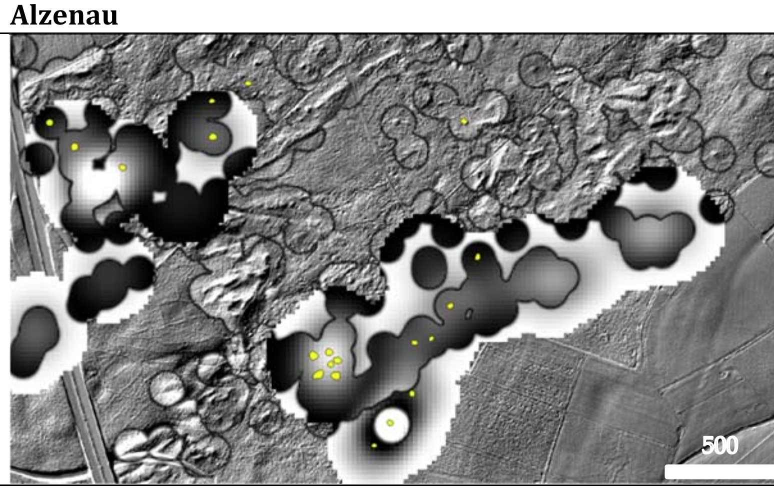
Both methods are semi-automatic from a point of view of cultural heritage agencies and agents, because it uses automated template matching and inexperienced volunteer selection by human interpretation. The patterns they reveal are interesting, and both help to statistically and more objectively classify landscape by circumstantial information extraction. Crowd-sourced data reveal macro patterns of contextual relations, while template matching reveal micro patterns of internal geometry composition. They both improve potentials of interpretation and classification, but combined they help substantiate recognition of areas of interest. However, product still necessitates finale experienced expertize classification of detection shapes and patterns. The results are therefore two methods for model based area understanding of landscape, by not focusing on individual details or features, and instead both producing macro patterns for dissemination and removing bias.

Applying the script for automated information extraction by templates is a simple task of operation for all interested parties. The major concern therefore becomes whether or not cost-efficiency and quality of information is improved. Crowd-sourced detection can be a time consuming task, but by volunteer basis not cost-consuming. The added positive is also creating and motivating a community of heritage enthusiasts capable of continued contribution, and individual surveying. This naturally requires infrastructure of logistics, but has been seen to produce very positive results in many countries with open heritage and remotely sensed data. The results of crowd-sourced and template matched data to reveal patterns and geometries of interest for cultural heritage management and detection is shown below in TABLE 23. The patterns are not completely similar, but the areas of overlap are extremely interesting, and the segmentation offers complete coverage of true burial mounds by combined effort.

TABLE 23: DETECTION PATTERN OF COMPARISON BETWEEN CROWD-SOURCED, TEMPLATE MATCHED, AND TRUE BURIAL MOUNDS BY SEGMENTATION TO AREAS OF INTEREST. GRADIENT IS INVERSED WITHIN TEMPLATE PATTERNS, MAKING THESE PATTERNS CONTRASTING REMAINING SEGMENTATION.

NAME	**Stockstadt am Main**
Verified BM Template pattern Gradient by Crowd-source pattern	
NAME	**Triefenstein**
Verified BM Template pattern Gradient by Crowd-source pattern	
NAME	**Hohe Wart**
Verified BM Template pattern Gradient by Crowd-source pattern	

NAME	**Amorbach**
Verified BM Template pattern Gradient by Crowd-source pattern	
NAME	**Kleinlangheim**
Verified BM Template pattern Gradient by Crowd-source pattern	
NAME	**Riedenheim**
Verified BM Template pattern Gradient by Crowd-source pattern	

NAME	**Maroldsweisach**
Verified BM Template pattern Gradient by Crowd-source pattern	
NAME	**Stettfeld**
Verified BM Template pattern Gradient by Crowd-source pattern	
NAME	**Alzenau**
Verified BM Template pattern Gradient by Crowd-source pattern	

Combining the methods in TABLE 23 reveals segmentation patterns containing burial mounds. At each site small differences in detection rates and patterns can be seen. From the site of Stockstadt, site no. 1, one cluster is not detected by template matching, but both crowd-sourced data and template matching missed true burial mounds. The false positives by the two methods are somewhat similar, but in general low. From the site of Triefenstein, site no. 2, all burial mound clusters are detected, with a lot of false positives from template matching due to modern construction and extreme slopes towards the river Main. The template matching show better detection of the northern group of burial mounds compared to crowd-sourced data, but all burial mounds are detected by both methods. At Hohe Wart, site no. 3, there is only one known burial mound in the vicinity, but the crowd-sourced data have increased amounts of false positives compared to template matching. Amorbach, site no. 4 also just contains one burial mound, and the detection of false positives is completely opposite between crowd-sourced and template matching, but both methods correctly detect the burial mound. From Kleinlangheim, site no. 5, the biggest rate of detection by both crowd-sourced data and template matching data, is centered on the known cluster of burial mounds. The template matching has many false positives located on the steep slopes towards the creek running across the landscape, while these peaks are completely excluded by the focus group. From the site of Riedenheim, site no. 6, both methods have strong correlation towards the burial mound cluster, and the focus group barely detects any false positives at the site. The template matching, however, shows many curvatures and elevations of interest, but also many along the roads in the open landscape and in the forest. From Maroldsweisach, site no. 7, the picture is very different, with the crowd-sourced data including many false positives, while the template matching barely extracts false positives, but misses one very flat burial mound. From Stettfeld, site no. 8, the situation is similar to Maroldsweisach with few false positives by the template matching, but many false positives by the focus group. However, the template matching also misses one hollowed “square” burial mound. At the last sample site, Alzenau, site no. 9, the landscape consist of peaked curvatures almost everywhere due to sand dunes. As a consequence, the template matching detects an extreme amount of false positives, but that is equal for the focus group. The template matching miss two verified burial mounds, but which are detected by the focus group. However, many unknown burial mounds are undoubtedly not verified in the field, and some of the areas detected by the template matching could certainly also be true burial mounds. At the site of Alzenau, finale verification requires archaeological excavation, but some good estimates can be done by the degree of similarity, combined with confidence value by selection from the focus group.

Both methods have missing true positives, but combined contain all known and verified burial mounds within the nine different sampling sites. Naturally, many of the false positive detections are not necessarily verified as non-existing, and can therefore consist of unknown features of curvature and elevation of interest towards complete detection of all burial mounds or cultural heritage within the landscape.

A complete picture of details of archaeological interest is impossible without archaeological excavation. The confidence of detection is as a result impossible to conclude, but undoubtedly the most prominent details of the landscape can be correctly selected and detected by remote investigations. Both methods equally have different potentials as untrained data segmentation of landscape into areas of interest, and best results are present when both methods are visualized before interpretation by expert classification of details in the landscape. Segmentation by crowd-sourcing and segmentation through template matching, delivers model based approaches for understanding the digital LIDAR landscape, as well as real physical entities in the terrain. The most interesting areas are undoubtedly when both methods overlap each other, however, in some areas there is a difference in detection due to differentiated focus on either micro or macro patterns. This is mainly visualized by the difference in false positive detection which diverts between the two methods. This also shows that, what computational are calculated as similar, are sometimes obvious for human cognition as not similar, and thus rejected. On the other hand, computational interpretation of landscape is not deceived by macro patterns in landscape, and sometimes reveals outliers that human cognition might miss because of expectancy to find a specific pattern. Rather, computational interpretation by templates, strictly focuses on the individual micro similarity of shape and curvature in the landscape compared to input. Similarly, input is changeable according to landscape, but the mound shape works correspondingly across many datasets if resolution and visualation of data remains the same.

The false positives of template matching often occur in complicated scenery, such as steep slopes, dynamic terrain or areas with heavy impact on landscape by modern use and manipulation. To filter out all areas of modern impact is complicated and controversial, because, then you also remove the areas most necessary to investigate due to more imminent danger. Human cognition easily excludes many apparent areas of non-interest, such as roundabouts, modern construction and many impacts of modern manipulation of landscape. At the same time, inexperienced and experienced human landscape interpretation, can quickly verify and reject many obvious automated template matching results. The automated segmentation of landscape, leads to detection of areas similar to rules defined, and this leads to objective investigation of data according to rules set in the parameters.

Differently to human interpretation, no areas will be forgotten by the computational segmentation of landscape. But the true classification of investigated subject might not always be completely true, but it offers the possibility to re-investigate and see landscape from a different perspective. Thus potentially, also leading to more correct and better verified monument detection by both desk based investigations and surveys.

Segmenting landscape by template matching also reveals some uncertainties in conclusion based on computational extraction alone. Two areas containing true burial mounds were not detected, but for all other sites the algorithm pinpointed areas of importance. Consequently, best approach would be by segmenting landscape into areas of interest, only then to judge and interpret details in the landscape. Similarly, crowd-sourced data does not deliver perfect segmentation and classification of landscape. However, the combined results improve the different methods, and thus inexperienced detection can produce knowledge generation by offering multiple perspectives, and perhaps detect and verify details not noticeable or not possible for the expert to investigate. Equally, the automated detection by similarity detects possible areas missed by expert interpretation. Because, what is sometimes revealed once archaeological excavation takes place, is that there are details that were almost impossible to notice before excavation, with only the slightest of curvature changes in terrain. Examples of such, are almost completely destroyed and overploughed burial mounds only present below topsoil. The end result of both crowd-sourced and computational data detection will never be perfect, but archaeological data and monuments in the landscape are not perfect. By applying semi-automatic information extraction for pattern recognition, cost efficiency and quality of information can be improved, because it reveals areas of interest to further investigate by experienced professionals, but also leads to investigation of areas potentially missed and undetected due to subjective expectation. The consequence of open data and increased perspectives by crowd-sourcing through public archaeology and computational segmentation and classification of landscape, are increased use and knowledge generation by combined efforts of multiple sources. Improved perspectives and potential collaboration for ground truthing by groups instead of individual experts increase the areas and perspectives possible to cover. Similar, computational segmentation and classification increase possibility of quicker verification by drawing focus to areas of interest, and thus minimizing the necessity to scan all details in large datasets. Likewise, more eyes on perspectives and context will only help safeguard the vulnerable monuments revealed and hidden in the landscape by increased detection, preservation, and protection by avareness and autonomous public presence in the landscape. Openness and cooperation is the only way forward. It is impossible for the archaeological community to keep track of all changes and destruction constantly affecting hidden and revealed information of archaeological sites and monuments. Consequently, aid is necessary to both track changes and undetected details still hidden. Such aid is possible to attain both by public archaeology through crowd-sourced data, but also automated pattern recognition to segment landscape into areas and details of interest necessary to investigate and re-investigate. Thus, it is a collaborative effort necessary to safeguard both the known and unkown details of landscape, and that is only possible with multiple perspectives and innovative methods of improving our knowledge gain. Knowledge gain by crowd-sourcing and automated procedures is by no means perfect, but it makes us look at landscape differently, and forces re-investigation of details sometimes overlooked. Therefore, the automation of archaeological monument detection certainly has an encouraging role as aid for heritage management, both now and in the future.

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6. CONCLUSIONS AND PERSPECTIVES

Throughout this thesis, conclusions and perspectives have been exemplified and created at the end of every chapter. Combined, they all offer different aspects to understand limitations and potentials of large-scale semi-automatic pattern recognition within an archaeological landscape. There are plenty of limitations, but the potentials are even greater.

Reliable spatial detection of archaeological monuments in the landscape, are necessary for large-scale cultural heritage management and detection. Resources for reliable spatial detection has been the goal of remote sensing in archaeology for a long time, but has been halted by the heterogeneous and imperfect nature of archaeological features in the landscape. With the increasing amount of remotely sensed data, and especially with the introduction of LIDAR, the needs for comparable and standardized approaches and methodologies have similarly increased. Meanwhile, our digital landscapes are archives of so many unknown details waiting to be detected and understood, but it is difficult to cost-efficiently investigate them all. The digital landscapes are manipulated products to reveal certain details of interest, but there is not enough time to actively investigate and interpret everything. The information of detail and information is too great to process, and our classification of landscape becomes subjectively blurred by what we are looking for. Semi-automatic pattern recognition by similarity matching and citizen science, are the methods for improving use of imperfect archaeological data to increase knowledge gain by improved quality of information. Semi-automated pattern recognition is also development of cost-efficient procedures for cultural heritage agencies and agents to detect and manage remnants of the past hidden and revealed in the landscape.

The field of automated information extraction is a dynamic field, rapidly improving, meanwhile open-data and open-source sharing is the standard in almost all aspects of public interest. Likewise, the trajectory of cultural heritage management and detection moves towards open-data and open-source sharing, resulting in increased use of data. The necessities are therefore also adaptation to amplified amounts of unsupervised and imperfect crowd-sourced data created by citizen science and public archaeology. The results of crowd-sourcing, can be improved quality of information, and thus deliver good detection rates for cultural heritage management. However, all landscapes and context are unique, meaning there is a constant need for adaptation to results. To handle large-scale information extraction, results needs to be standardized and comparable. To adapt, it is necessary to compromise and segment information into qualified standards in order to extract information for improved knowledge gain. However, there are so many different aspects of large-scale cultural heritage management and detection, that it can be difficult to visualize necessities and problems. This thesis was written to represent and visualize many different aspects of large-scale cultural heritage management and detection with the intent of discussing and defining archaeological LIDAR potential and limitations, visualizing the imperfect nature of archaeological monuments, representing the field of automated detection within archaeology, and semi-automatic extraction of information from crowd-sourced and automated template matching. This is presented in six chapters, all offering different aspects on how to understand the digital LIDAR landscape of the past and present, and how the trajectory of automated information extraction develops. For this purpose:

Chapter 1 defines the thesis outline, premise, and motivation. **Chapter 2** focuses on technical aspects of LIDAR data and archaeological LIDAR use and potential. The chapter explains history, development, and defines the LIDAR product from point to plane. From initial outline of the LIDAR product, the chapter exemplifies how archaeological LIDAR can be improved by adding information. The extent of LIDAR goes from passive sensing to active sensing, with added, altered, or intensified wavelengths. But too much information can equally disturb the possibilities for human cognition and computational calculation to interpret details. Optimal settings are therefore not found by always improving resolution, because the increased amount of details blurs the macro patterns possible to discern in digital elevation models. Standards for comparison of data are also complicated by the diversity of LIDAR data and metadata, making for necessities of calibration and normalization to assess between different LIDAR datasets. This can be controlled by interpolation and visualization, however, amount of detail can still complicate comparison. When defining interpolation and visualization of data, it is necessary to remember that different means of interpolation and visualization makes for detection of dissimilar features and structures in the landscape. The commonly applied presentation of digital elevation models are by visualizing relief shade or hillshade. Shading landscape by relief is easily understandable for human cognition, and therefore often a standard chosen for visualization of LIDAR data for crowd-sourced information extraction. Shading landscape by relief is equally machine readable, and the case studies are therefore represented by similar relief shading for comparison. However, LIDAR accessibility can complicate possibilities for archaeologist and engaged public alike, resulting in difference by lack of use, cost-efficiency, and quality of information extracted.

Chapter 3 represented primary data for information extraction. Specifics and definition of data and metadata structure was introduced to explain steps of procedure for the complete interpolation of the dataset from Lower Franconia. To understand the dataset from Lower Franconia, it is necessary to explain and model composition of features in the landscape by the imperfect nature of archaeological data. Because, no matter the approach for segmenting landscape, individual data points are distorted and skewed by the impact of cultural and natural manipulation of landscape, combined with decomposition, degradation, and decay of patterns of the past and present. Micro patterns are therefore illusive and difficult to confidently determine by desk-based investigations, while macro patterns fade by lack of overview through surveying. Different approaches reveal different details, but it is necessary to establish best steps of processing to improve both field and desk based investigations. Segmentation of landscape before surveying improves the possibility of investigating individual details, while understanding macro patterns in landscape, resorting to discovery of additional details in the landscape. However, not all micro patterns detected by desk based investigations are true, because terrain and surface is in constant transition.

Chapter 4 defines the field of automated information extraction by remotely sensed data, with particular focus on extraction of archaeological features and structures from LIDAR data. The field of automated segmentation and classification of details in remote sensing is undoubtedly growing. However, within the archaeological community for cultural heritage management and detection, the pattern is not as defined. Undoubtedly, the archaeological community is seeing a network grow and develop for automated and semi-automated means of detection, with certain leading brokers and institutions influencing the field. By people and articles influencing the field, state of the art and best practice can be established by common use and trends of use. The NA shows that data driven approaches were previously much more prevalent, but the articles and authors leading the field are adapting to model driven approaches and template matching. Four research entities were detected by pattern of community influence on the field. By dynamic time-scaled representation of research and articles the evolution of the field is extracted by key instigators, brokers, and leaders. The pattern of present field development is used as representation for methodology to define state of the art and best practice. The results on methodology are applied in the following chapter for automated information extraction and archaeological monument detection in LIDAR data.

Chapter 5 applies visual detection, citizen science by crowd-sourcing data, and automated information extraction to segment and classify landscape. The results vary, but all contain different potentials and limitations. The two approaches discussed are extracted from the conclusions of chapter 4, and consist of automated information extraction by data or model driven approaches. This implies information extraction by per pixel or by geometry and regions. Means of information extraction can adapt many different variables of data, but easily becomes intricate to a degree where amount of information distorts more than aids the possibilities of improving quality of information. In contrast, simple information extraction by template matching offers a good rate of detection by similarity validation. Equally, citizen science through crowd-sourced data offers a good rate of detection by relative confidence defined by selection count. Comparing the two methods of simple information extraction through crowd-sourced data and template matching, indicates interesting detection patterns of landscape interpretation. The patterns are to a strong degree dissimilar by selection of either micro or macro patterns in landscape. However, where the two methods overlap, the confidence of detection is greatest. By combined segmentation, all true burial mound areas of interest are detected, with new areas of interest modelled, and areas containing false positives more easily excluded. The resulting automated information extraction is not perfect, but it offers an enhanced segmented perspective on micro and macro patterns in the landscape.

From all the different chapters, different perspectives are given for semi-automatic pattern recognition within an archaeological landscape. The basis of the thesis is to present opportunities for large-scale cultural heritage management and detection. This also implies creating more objective and comparable datasets in combination for knowledge-based expert interpretation and automated procedures of information extraction of real entities and details in the landscape. For detection of archaeological monuments in LIDAR data, best results of positive detection are by expert interpretation combined with differentiated perspectives and fieldwork. But all human interpretation of characteristics and variables within a given dataset can also be incorrect due to misclassification based on external and internal influence and bias. By computation, however, the results are controlled and replicable. Computational detection confronts the same problems as visual detection with a high degree of false positive detections with indiscriminate segmentation and classification, and both approaches have high uncontrolled error rates of detection if not proper organized and adjusted. The real concern is therefore how to prober optimize and adjust weights to increase time efficiency for optimal large-scale segmentation and classification of landscape. By computation for archaeological detection and mapping, the real objective is to improve quality of information towards confident true positive detections, rather than removing the human component. This is especially true for the diverse pattern of imperfect archaeological monuments hidden in the modern landscape. Aimed at optimizing positive detection of a specific structure or pattern from the past, it is a matter of improving efficiency by minimizing errors based on performance evaluation through input and expected output. Thus, automated detection for archaeological features and structures is not necessarily a matter of absolute detection, but rather of best fit to the archaeological community by minimizing error rates or improving confidence. This statement also implies that the human interpreter should not be removed for the applied means of detection, but rather that computation should focus on how to optimize the procedures to quantifiably and objectively determine the extent and possibilities for improved detection rates for the human interpreter. Because, the patterns of archaeological features and structures, necessitates discarding similar patterns in the landscape constructed by natural and cultural activity. This is especially true for the detection of tumuli, since barrows and mounds are continuously created by cultural and natural activities of different purposes creating similar patterns equal to burial mounds of the past. Generally, within the archaeological community, one of the assumptions is that the techniques thus far have not provided improved detection rates and proper classification of archaeological monuments in the landscape to effectively remove the human involvement in archaeological mapping and management. The archaeological community is questioning whether or not it will be computational possible to replicate and imitate the human interpreter (Parcak 2009, 110). Due to the imperfect nature of archaeological remains in the landscape. This is a valid and proper critique, but not necessarily the correct concern. Because, even though automated mapping of archaeological monuments might never be fully automated, the procedures are still improving the potential of archaeological detection and management. Some concerns determine that the imperfect nature of archaeological data makes for too many false positives while omitting patterns of interest by automated detection (Hanson 2010). Equally, this is a valid concern, but not necessarily the correct concern. The reason for this is: one approach does not omit the other, but rather should be used and seen as a dual approach of investigation. In the end, the result is always measured by the input parameters, and thus a matter of learning how to cognitively or computationally understand and describe the landscape. This entails that the outcome will always be, manually and automatically, a result based on prior knowledge of already known parameters. However, even by mapping or detecting already known and recurrent archaeological monuments in the landscape, this improves the possibility of detecting atypical and unknown monuments in the landscape by providing additional resources by which patterns can be distinguished. Thus by measuring potential use and application within archaeological landscapes, the core of implementation lies perhaps not in the classification of details, but rather in the segmentation for improved information extraction by aiding pattern recognition. The added layers of segmentation changes interpretation of landscape, and thus helps to define the variables of the near infinite diversity by which archaeological monuments can be described. This in return constructs the spatial record on how the landscape of the past should be understood, outlining indices and geometries possible to compute and interpret, or segment and classify. By using simple untrained and unsupervised automatic information extraction, it is possible to achieve good results for segmenting landscape into areas of interest for improved human visual detection and verification. Equally, by using simple untrained and unsupervised crowd-sourced information extraction, it is possible to achieve good results for segmenting landscape into areas of interest. Combined, detection becomes almost similar to expertly defined and detected monument detection and extraction of information in the landscape. This should not be seen as a threat to experts in the field, but rather as an improved perspective that can be used by experts. The proposed dual methods of simple information extraction creates a baseline dataset by combined micro and macro patterns of features and areas of interest to aid and safeguard cultural heritage in the landscape.

Certainly, the imperfect nature of archaeological data is a continued concern for archaeological monument detection and mapping, but the concern is similar for both manual and automatic information extraction of details in the landscape. In the end, one set of unique values for archaeological monuments do not exist, but they are scattered on a scale from 0 to 1. Within the range of 0 to 1 lies infinite variation in finite space, similar to cultural heritage monuments hidden and revealed in the landscape. All finite definition is a compromise to compare and standardize interpretation, but can always differ based on perspective. Therefore, segmentation is the compromise between infinite values or perspectives to finite values and perspectives to classify, define, and describe entities, and ideas. Every possibility of improving our understanding of entities and ideas should be accepted, because they can always be expanded and elaborated. Segmenting and classifying our landscape helps increase the scale of definition for both human and computational understanding, and by simple semi-automatic information extraction, our landscapes can be much better understood for improved knowledge generation towards large-scale cultural heritage management and detection.

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Appendix 3A

BMID	Area	Cluster	BMID	Area	Cluster	BMID	Area	Cluster
1	Stockstadt am Main	1	40	Hohe Wart	1	110	Maroldsweisach	1
2	Stockstadt am Main	1	41	Amorbach	1	111	Maroldsweisach	1
3	Stockstadt am Main	1	42	Kleinlangheim	1	113	Maroldsweisach	1
4	Stockstadt am Main	1	43	Kleinlangheim	1	120	Maroldsweisach	2
5	Stockstadt am Main	1	44	Kleinlangheim	1	121	Maroldsweisach	2
6	Stockstadt am Main	2	45	Kleinlangheim	1	122	Maroldsweisach	2
7	Stockstadt am Main	2	46	Kleinlangheim	1	123	Maroldsweisach	2
8	Stockstadt am Main	2	47	Kleinlangheim	1	124	Maroldsweisach	2
9	Stockstadt am Main	2	48	Kleinlangheim	1	125	Maroldsweisach	2
10	Stockstadt am Main	3	49	Kleinlangheim	1	126	Maroldsweisach	2
11	Stockstadt am Main	3	50	Kleinlangheim	1	130	Stettfeld	1
12	Stockstadt am Main	3	51	Kleinlangheim	1	131	Stettfeld	1
15	Triefenstein	3	52	Kleinlangheim	1	140	Alzenau	1
16	Triefenstein	1	53	Kleinlangheim	1	141	Alzenau	1
17	Triefenstein	1	54	Kleinlangheim	1	142	Alzenau	1
18	Triefenstein	1	55	Kleinlangheim	1	143	Alzenau	2
19	Triefenstein	1	56	Kleinlangheim	1	144	Alzenau	2
20	Triefenstein	2	57	Kleinlangheim	1	145	Alzenau	2
21	Triefenstein	2	58	Kleinlangheim	1	146	Alzenau	2
22	Triefenstein	2	59	Kleinlangheim	1	147	Alzenau	2
23	Triefenstein	2	60	Kleinlangheim	1	148	Alzenau	2
24	Triefenstein	2	61	Kleinlangheim	1	149	Alzenau	2
25	Triefenstein	2	62	Kleinlangheim	1	150	Alzenau	2
26	Triefenstein	2	63	Kleinlangheim	1	151	Alzenau	2
27	Triefenstein	2	64	Kleinlangheim	1	152	Alzenau	2
28	Triefenstein	2	65	Kleinlangheim	1	153	Alzenau	2
29	Triefenstein	2	70	Riedenheim	1	154	Alzenau	2
30	Triefenstein	2	71	Riedenheim	1	155	Alzenau	2
31	Triefenstein		72	Riedenheim	1	156	Alzenau	2
32	Triefenstein		73	Riedenheim	1	157	Alzenau	2
33	Triefenstein	3	74	Riedenheim	1	158	Alzenau	2
34	Triefenstein	3	75	Riedenheim	1	159	Alzenau	2
35	Triefenstein	3	76	Riedenheim	1	160	Alzenau	2
36	Triefenstein	3	77	Riedenheim	1	161	Alzenau	2
37	Triefenstein	3	78	Riedenheim	1	162	Alzenau	1
38	Triefenstein	3	79	Riedenheim	1	163	Alzenau	1
39	Triefenstein	3	80	Riedenheim	1	164	Alzenau	1

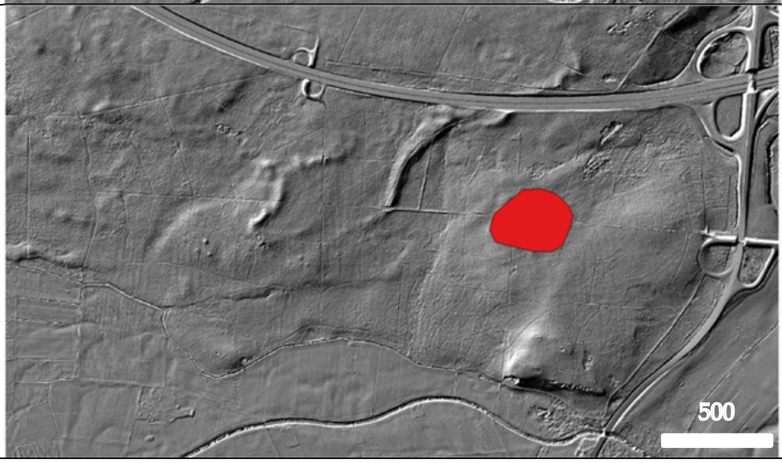
Appendix 3B

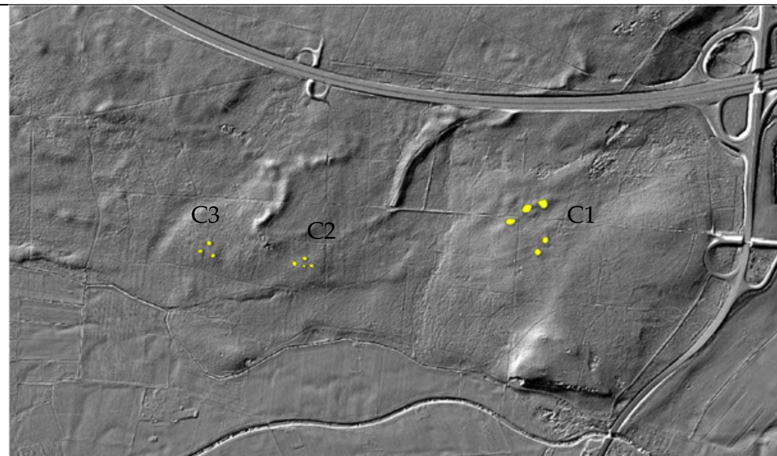
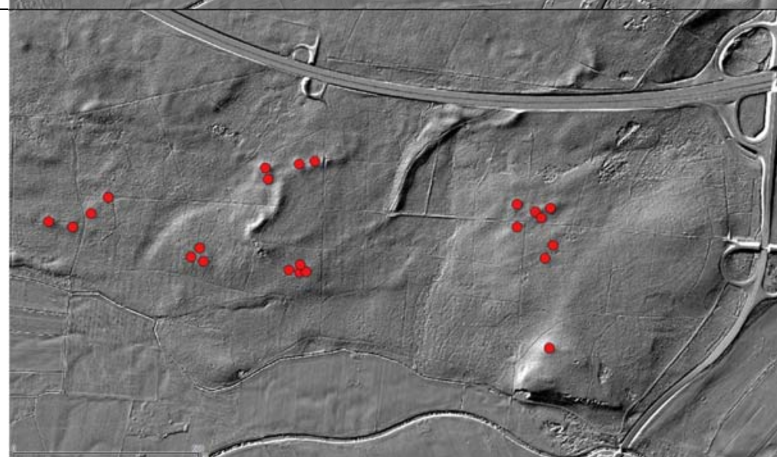
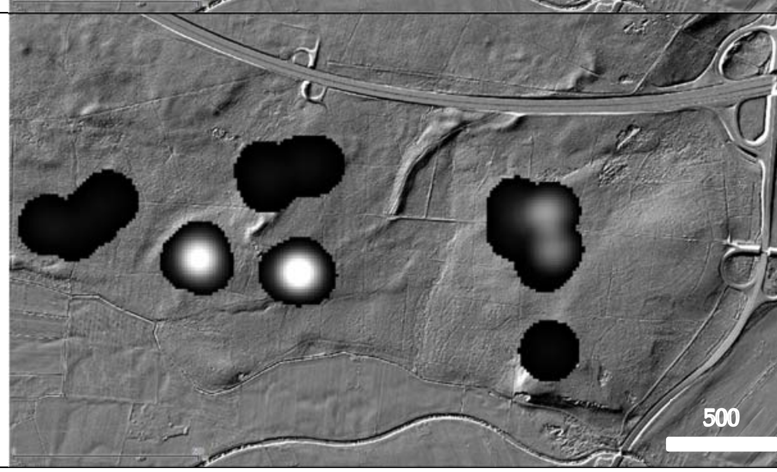
NAME	Stockstadt am Main
Description	Burial mounds; three clusters
Temporal or cultural frame	Unknown prehistory
Ground truth estimate	12
Nearest administrative UID	207688
File number	D-6-6020-0087
Sub district	361

Description:

12 burial mounds were located by field inspection. The 12 burial mounds are located in three distinct clusters, C1-3, but all are placed on the ridge towards the valley to the south. The burial mounds to the east, C1, are all heavily damaged by looting and a road running through one of them. All mounds in C1 are larger. The burial mounds in C2 are almost not noticable in the field due to canopy obstrcution, but stands out as patterns of clear cultural certainty within the DEM. The last cluster, C3, are quite prominent in the DEM as well as in the landscape, but all have also been looted at some point in time.

Visual detection

Raw relief shade Sun zenith: 45 Sun azimuth: 315	
Burial cemetery recorded on site	

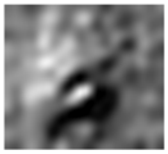
Burial mounds confirmed by field inspection	
Survey results for visual detection	
Survey results for visual detection by kernel density. Radius 100, Cellsize: 10 Weight: count Gradient: black to white from less to more	

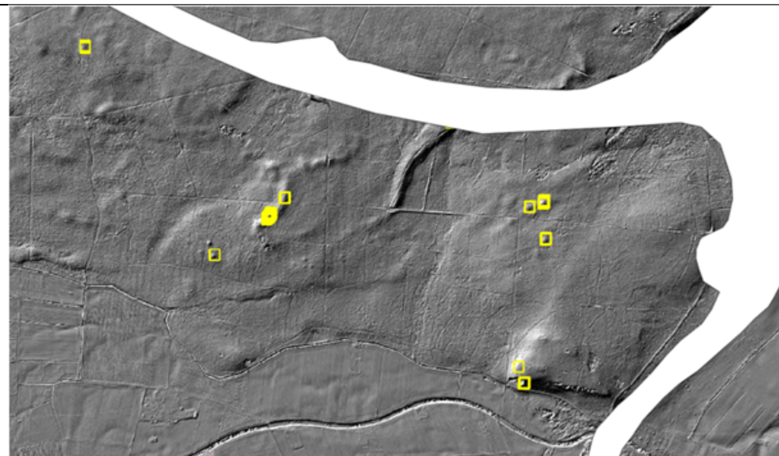
COEFF_N

Threshold val:

0.5

Template:

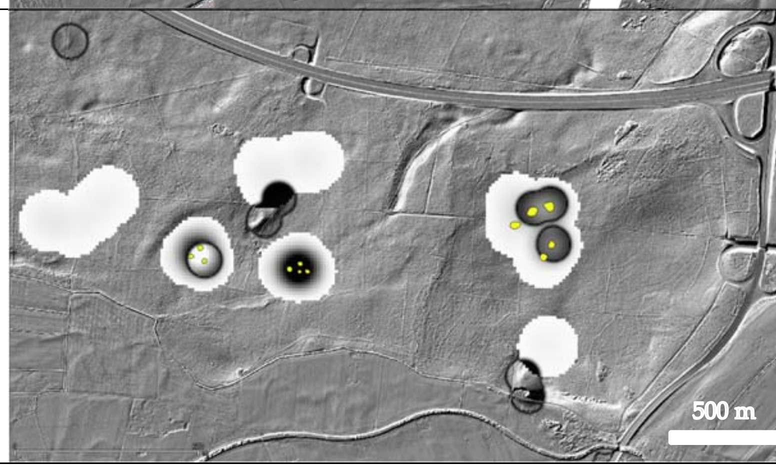




Verified BM

Template pattern

Gradient by Crowd-source pattern



<table>
<tr><td>BM1
C1
View: NE

Note:
largest
mound of
Group1

GK4:
4287947/
5542874

[6113]</td><td></td></tr>
<tr><td>BM1
C1
View: N

Note:
negative
openness
of BM
looting

GK4:
4287947/
5542874

[6117]</td><td></td></tr>
</table>

BM3 C1 View: SE Note: slight unnatural elevation cut by road. GK4: 4287839/ 5542817 [6131]	
BM4 C1 View: SV Note: beginning line of BM GK4: 4287954/ 5542751 [6132]	

BM4 C1 View: N Note: Middle of BM with looting cut GK4: 4287948/5542768 [6138]	
BM6 C2 View: S Note: largest BM of C2 GK4: 4287159/ 5542665 [6167]	

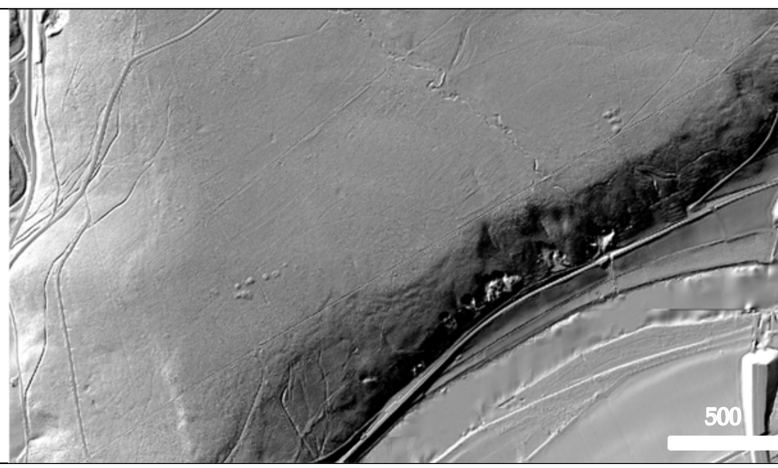
BM12 C3 View: SE Note: BM with looting cut in the middle GK4: 4286822/ 5542698 [6163]	
BM10 C3 View: N Note: Most western BM. Flat, but no traces of looting GK4: 4286779/ 5542714 [6162]	

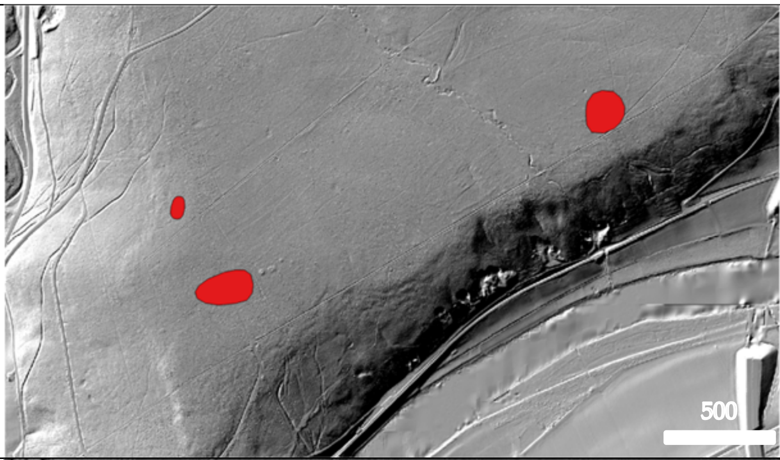
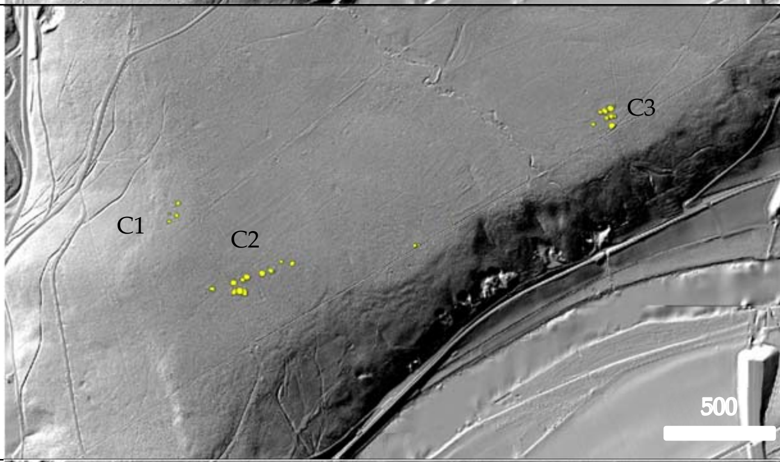
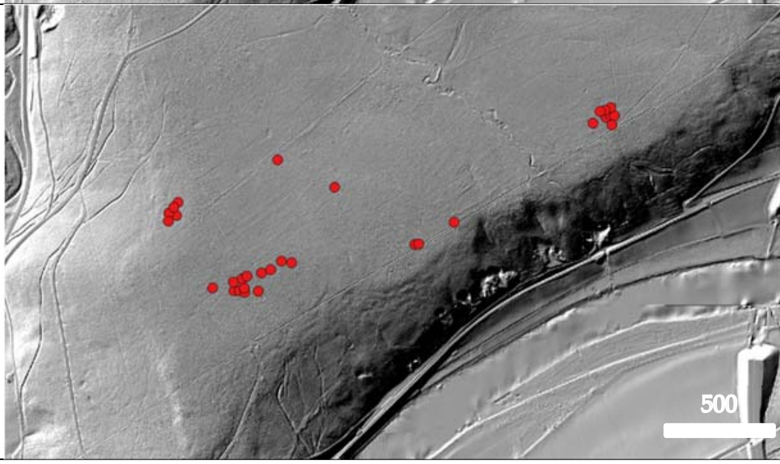
NAME	Triefenstein
Description	Burial mounds; three clusters
Temporal or cultural frame	Unknown prehistory
Ground truth estimate	25
Nearest administrative UID	199043; 208622; 982209
File number	D-6-6223-0013; D-6-6223-0012; D-6-6223-0049
Sub district	613

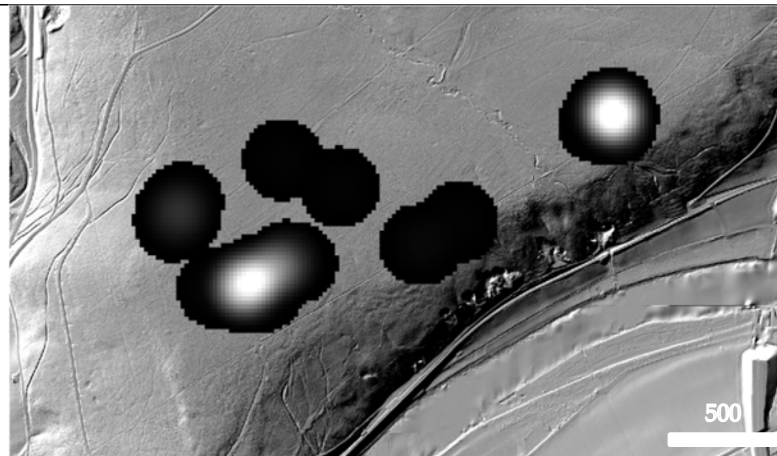
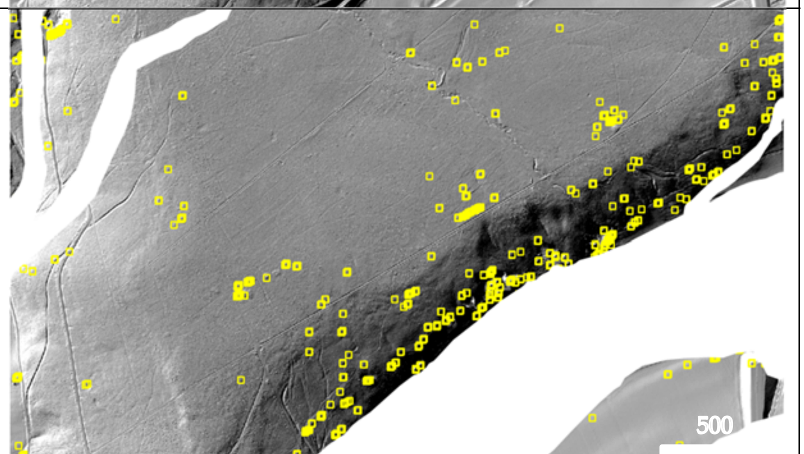
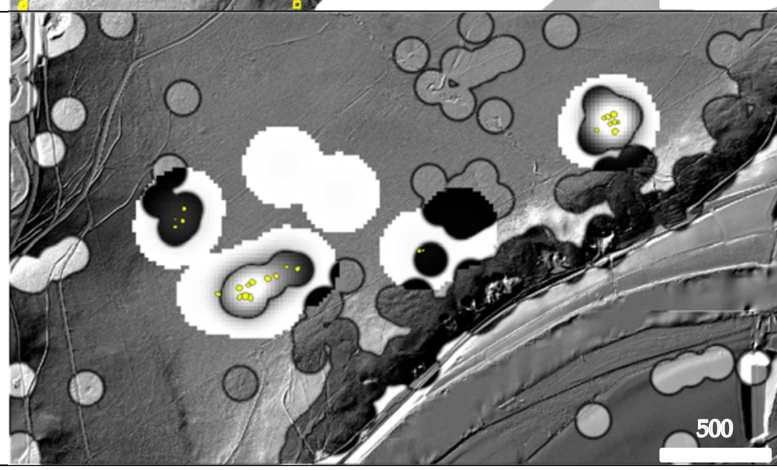
Description:

Three distinct clusters of burial mounds, all located on the same plateau above the river Main, near Urphar. C1 consist of four flat topped burial mounds. C2 consist of minimum 11 burial mounds with some being cut by a pathway. Within the centre of the concentration the burial mounds are overlapping eachother, but it is difficult to assess stratigraphic relations without formal excavation. However, it does seem like the two burial mounds in the centre are the primary connectors. In between C2 and C3, some smaller circular earthenwork are also present as potential burial mounds, but they are all connected to the forest roads, and therefore might as well be connected to general earthenwork construction due to logistic patterns of waste dispersal. The last group C3, consist of a minimum of eight burial mounds of varying size, and are stratigraphicly overlapping. The temporal scope of the grave fields are undocumented, but a connection to the Migration Age fortification of Wettenburg is likely due to spatial presence within close vicinity.

Visual detection

Raw relief shade Sun zenith: 45 Sun azimuth: 315	

Burial cemetery recorded on site	
Burial mounds confirmed by field inspection	
Survey results for visual detection	

Survey results for visual detection by kernel density. Radius 100, Cellsize: 10 Weight: count Gradient: black to white from less to more	
COEFF_N Threshold val: 0.55 Template: 	
Verified BM Template pattern Gradient by Crowd-source pattern	

BM16 C1 View: W Note: Very flat topped elevation GK4: 4323799/ 5519310 [6203]	
BM22 C2 View: NE Note: Start of the larger C1 concentrati on GK4: 4323935/ 5519122 [6206]	

BM23 C2 View: W Note: Large BM connected with many smaller GK4: 4323954/ 5519127 [6208]		
BM26 C2 View: E Note: Large BM connected with many smaller GK4: 4323971/ 5519161 [6208]		

BM28 C2 View: E Note: Extension of C2 towards east GK4: 4324030/ 5519176 [6218]	
BM31 View: N Note: One of the less distinct elevations in between C2 and C3 GK4: 4324383/ 5519238 [6220]	

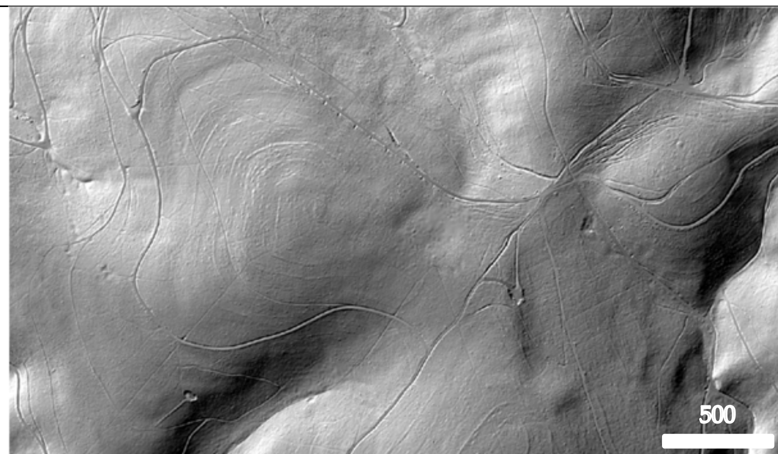
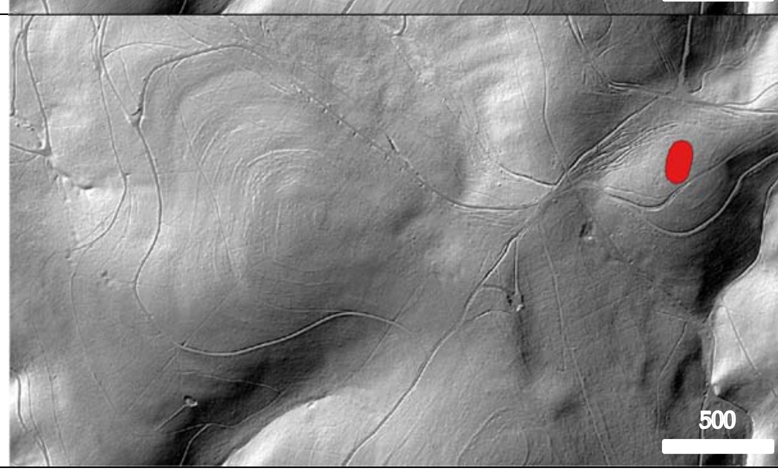
BM35 C3 View: N Note: Towards the two rows of BMs GK4: 4324868/ 5519532 [6228]	
BM41 C3 View: NE Note: Last row of BMs GK4: 4324864/5 519573 [6243]	

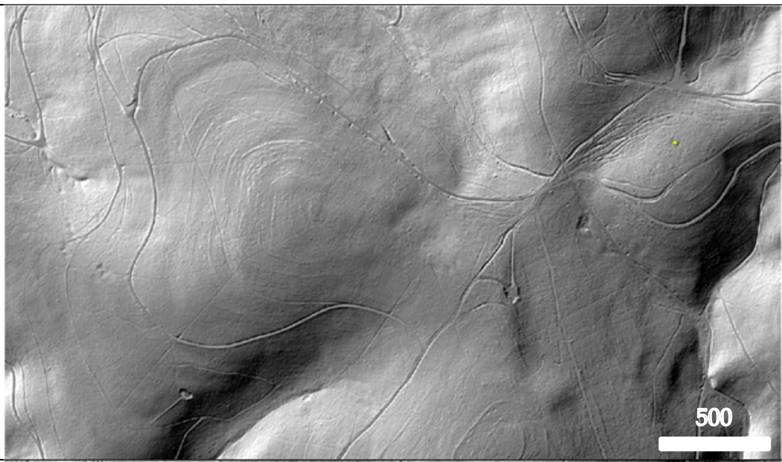
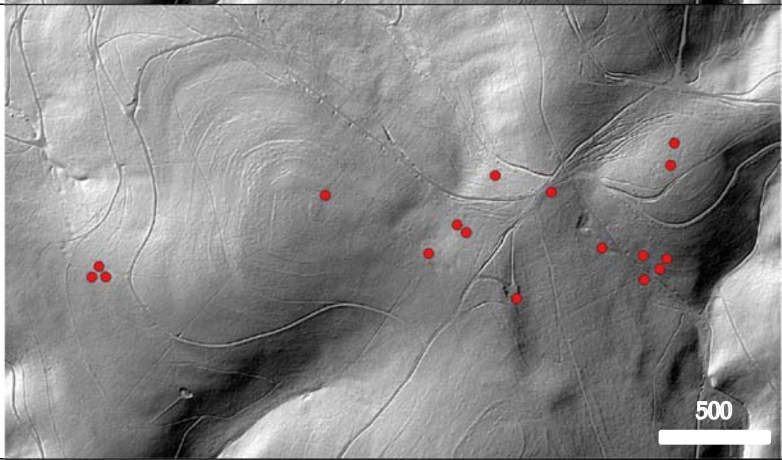
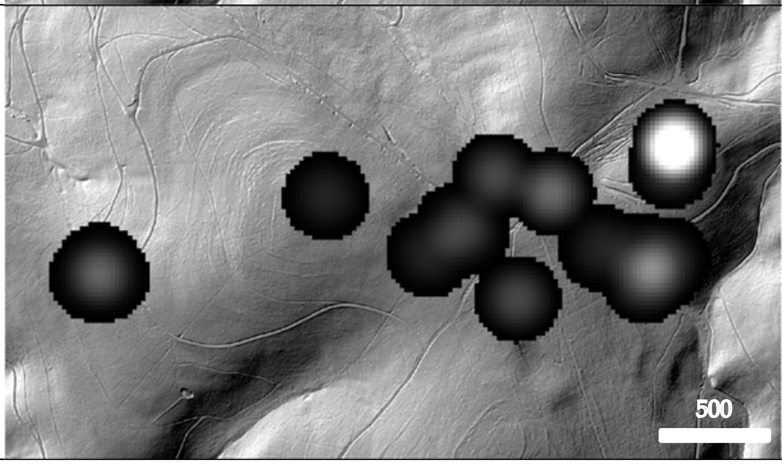
NAME	**Hohe Wart**
Description	Burial mound; one cluster
Temporal or cultural frame	Unknown prehistory
Ground truth estimate	1
Nearest administrative UID	977096
File number	D-6-6021-0094
Sub district	406

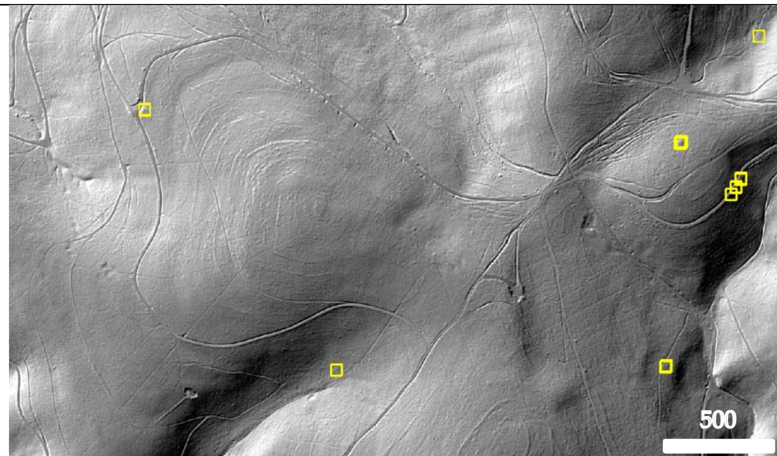
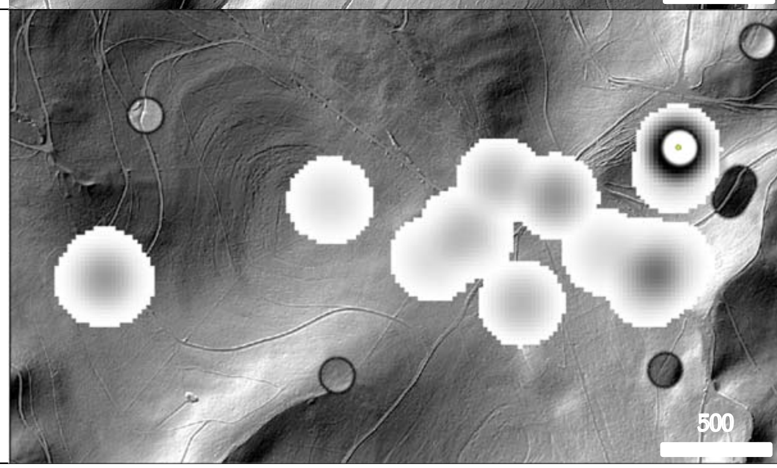
Description:

The burial mound of Hohe Wart, is a singular regocnisable mound located on a very steep slope on a hillside facing the north. By its physical presence, it stands out as a compact earthenwork covered with stones.

Visual detection

Raw relief shade Sun zenith: 45 Sun azimuth: 315	
Burial cemetery recorded on site	

Burial mounds confirmed by field inspection	
Survey results of manual visual detection	
Survey results for visual detection by kernel density. Radius 100, Cellsize: 10 Weight: count Gradient: black to white from less to more	

COEFF_N Threshold val: 0.5 Template: 	
Verified BM Template pattern Gradient by Crowd-source pattern	

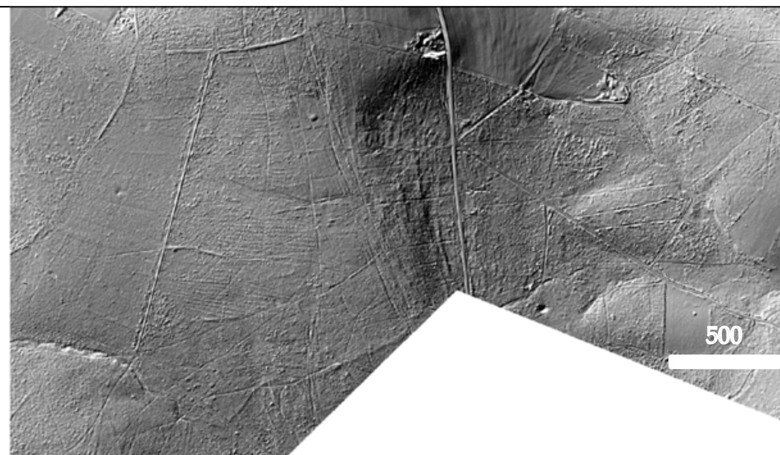
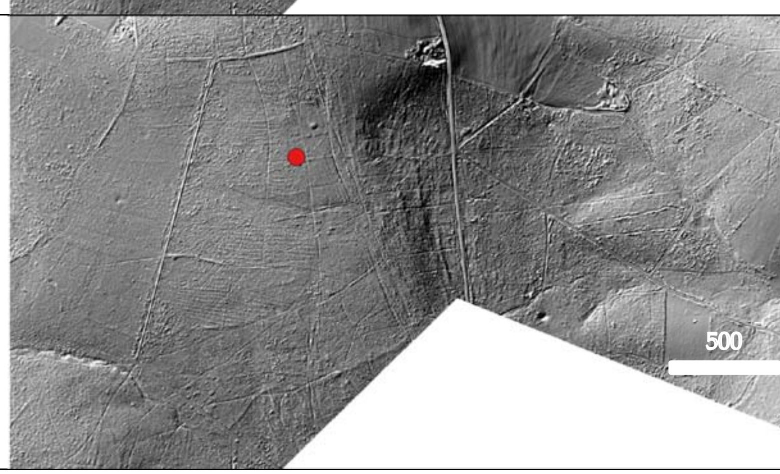
BM40 C1 View: W Note: Stone covered BM GK4: 4302744/ 5534815 [6183]	
BM40 C1 View: W Note: Stone covered BM GK4: 4302744/ 5534815 [6184]	

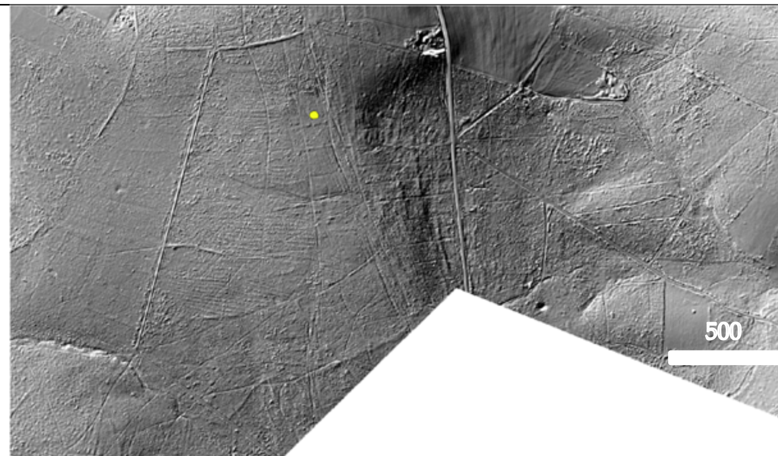
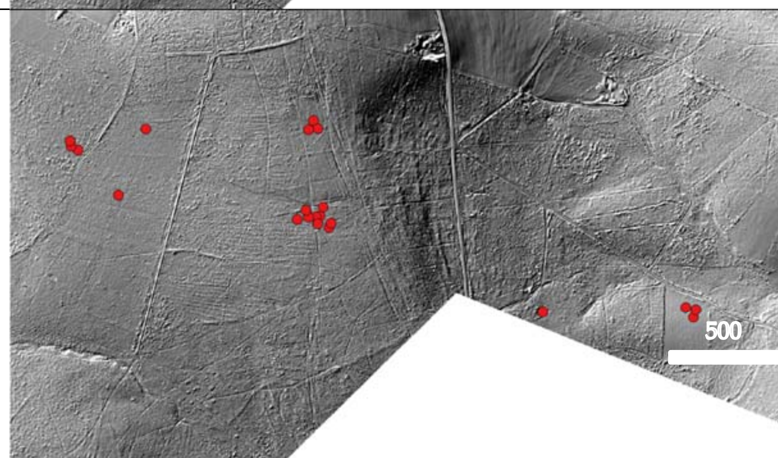
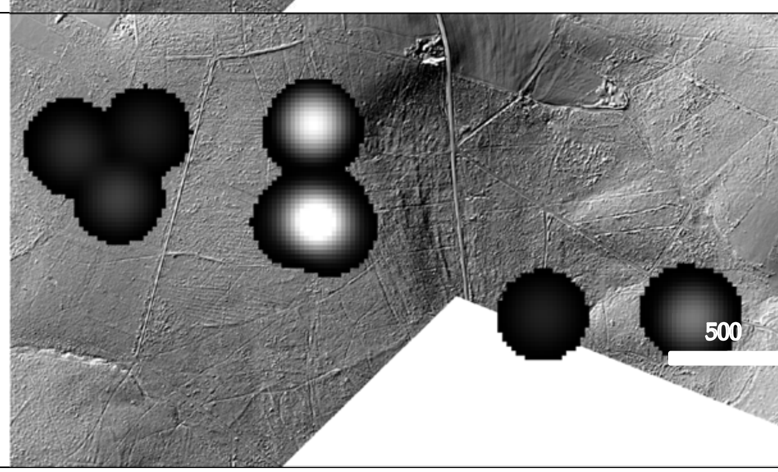
NAME	**Amorbach**
Description	Burial mound; one cluster
Timeframe	Unknown prehistory
Ground truth estimate	1
Nearest administrative UID	201173
File number	D-6-6321-0004
Sub district	470

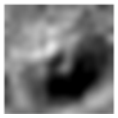
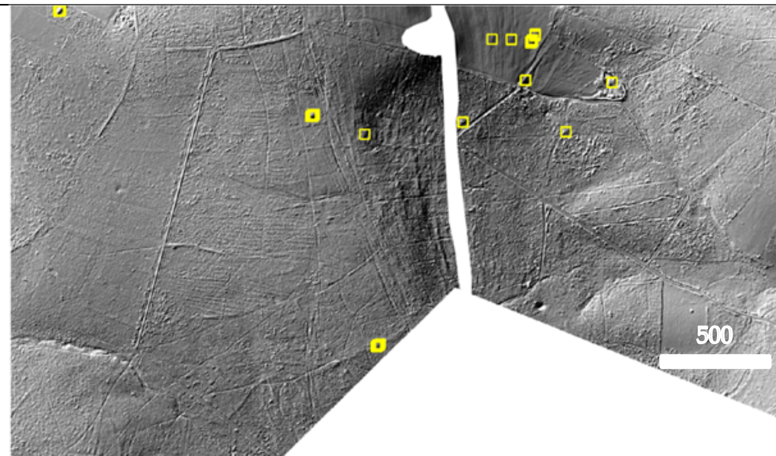
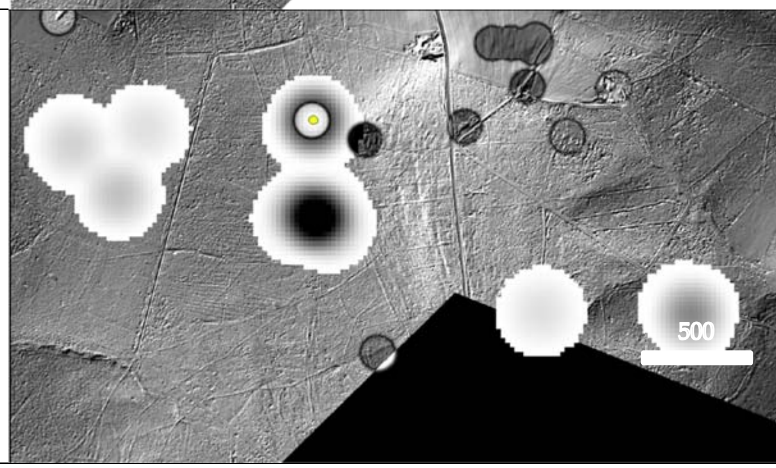
Description:

The burial mound of Amorbach lies singuarly near the highest topographic point in the landscape. Forestry is very active, and fresh tractor tracks were seen dug into the side of the burial mound.

Visual detection

Raw relief shade Sun zenith: 45 Sun azimuth: 315	
Burial cemetery recorded on site	

Burial mounds confirmed by field inspection	
Survey results of manual visual detection	
Survey results for visual detection by kernel density. Radius 100, Cellsize: 10 Weight: count Gradient: black to white from less to more	

COEFF_N Threshold val: 0.5 Template: 	
Verified BM Template pattern  Gradient by Crowd-source pattern	

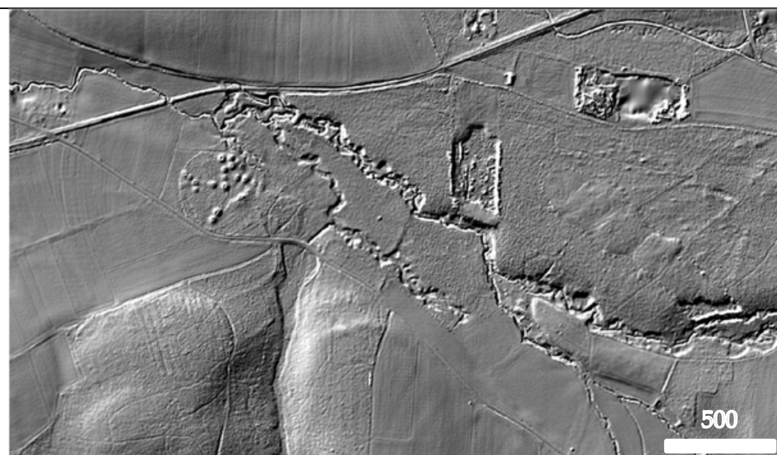
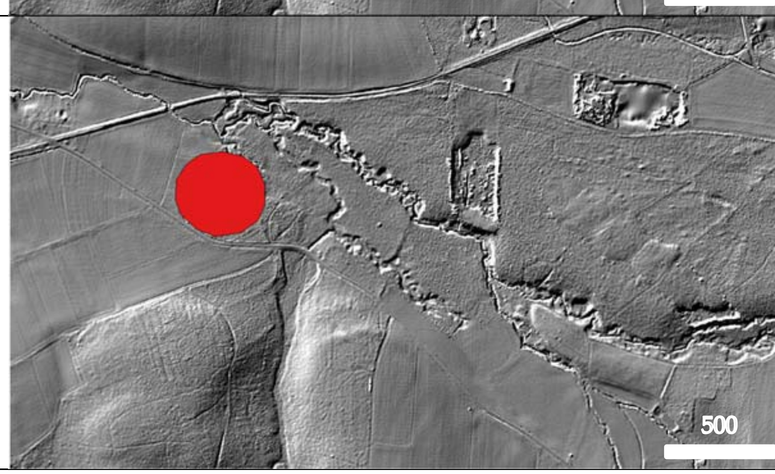
BM41 C1 View: N Note: Flat topped, but with a large diameter GK4: 4305460/ 5505326 [6188]	
BM41 C1 View: E Note: Flat topped, but with a large diameter GK4: 4305460/ 5505326 [6191]	

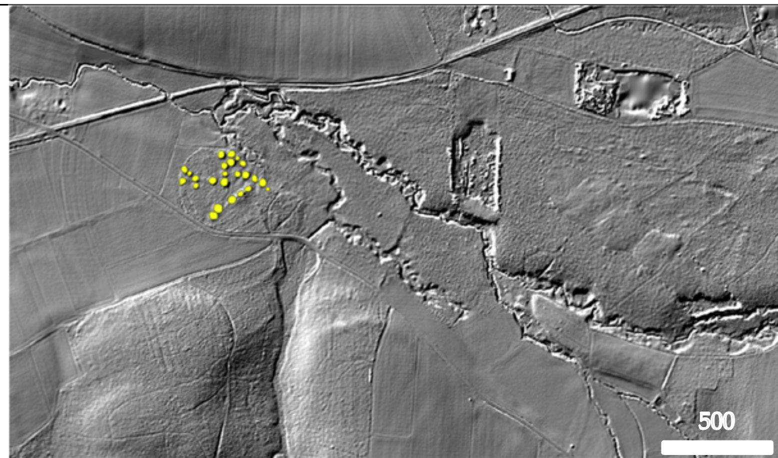
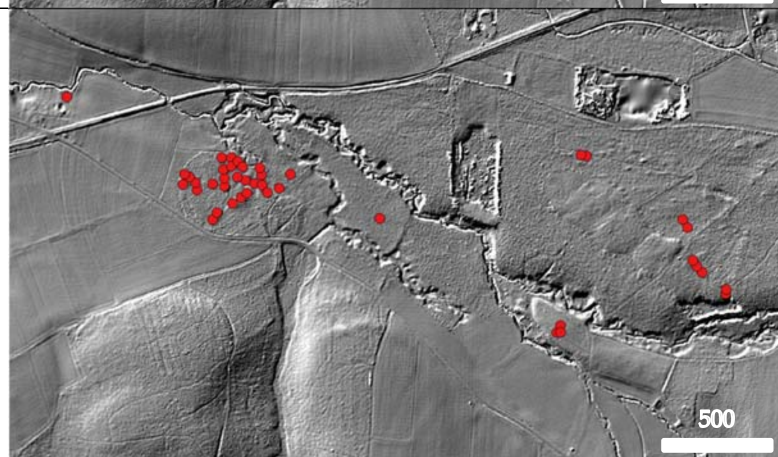
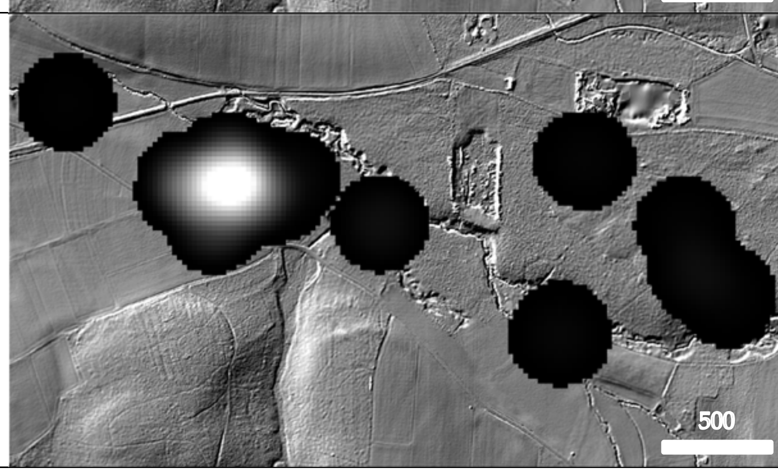
NAME	**Kleinlangheim**
Description	Burial mounds; one cluster
Timeframe	Hallstatt Culture
Ground truth estimate	26
Nearest administrative UID	209040
File number	D-6-6227-0058
Sub district	1154;1142

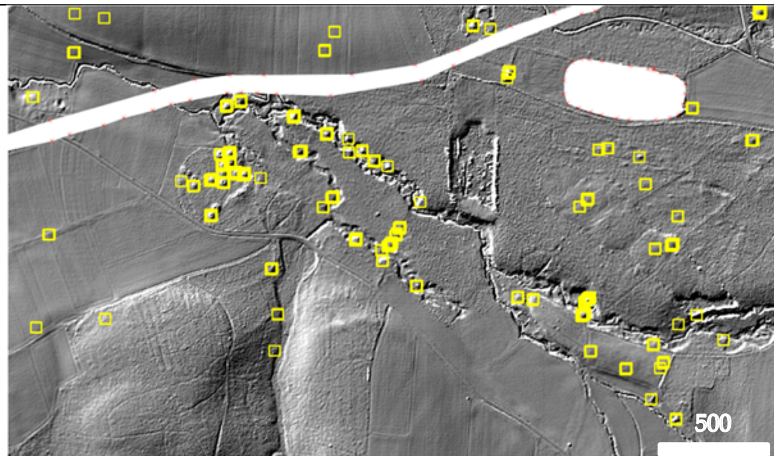
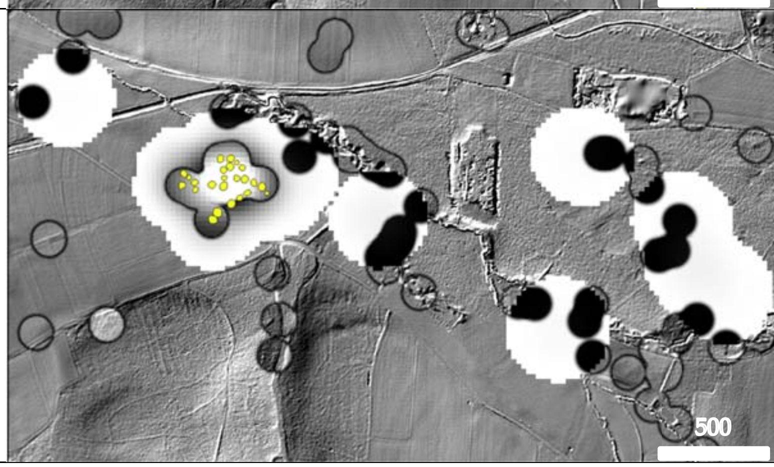
Description:

One large cluster of burial mounds with different degrees of preservation. Some older, and some more modern evidence of looting and digging in the landscape. West of the burial mound concentration, several potential overploughed burial mounds were identified due to slight elevation, and the discovery of ceramics of potential Hallstat Culture. Other finds of Hallstat Culture has been located in the vicinity, and is a likely connection to the burial mounds. The burial mounds are located in the small valley, almost at the lowest point in the vicinity, but with slight elevation towards the south.

Visual detection

Raw relief shade Sun zenith: 45 Sun azimuth: 315	
Burial cemetery recorded on site	

Burial mounds confirmed by field inspection	
Survey results of manual visual detection	
Survey results for visual detection by kernel density. Radius 100, Cellsize: 10 Weight: count Gradient: black to white from less to more	

COEFF_N Threshold val: 0.6 Template: 	
Verified BM Template pattern Gradient by Crowd-source pattern	

<table>
<tr><td>BM63
C1
View: SW

Note:
Two connected BMs on the southern edge of the cluster

GK4:
4378948/
5517293

[6251]</td><td></td></tr>
<tr><td>BM62
C1
View: NW

Note:
Deep cut in BM62

GK4:
4378956/
5517307

[6255]</td><td></td></tr>
</table>

BM62 C1 View: N Note: Middle of the cluster towards western edge GK4: 4378956/ 5517307 [6257]	
BM48 C1 View: NW Note: Middle of the cluster towards western edge GK4: 4378970/ 5517360 [6259]	

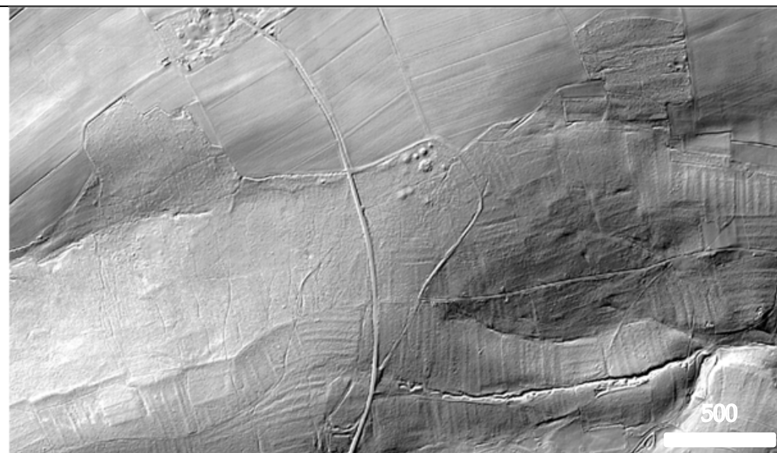
BM46 C1 View: N Note: Modern cut GK4: 4378945/ 5517365 [6262]	
Anomaly View: N Note: A anomaly reflected as a mound within the DTM GK4: 4379285 5517295 [6263]	

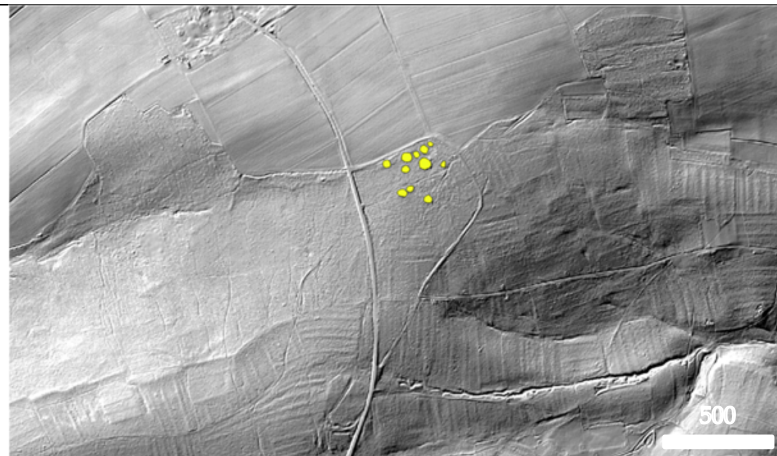
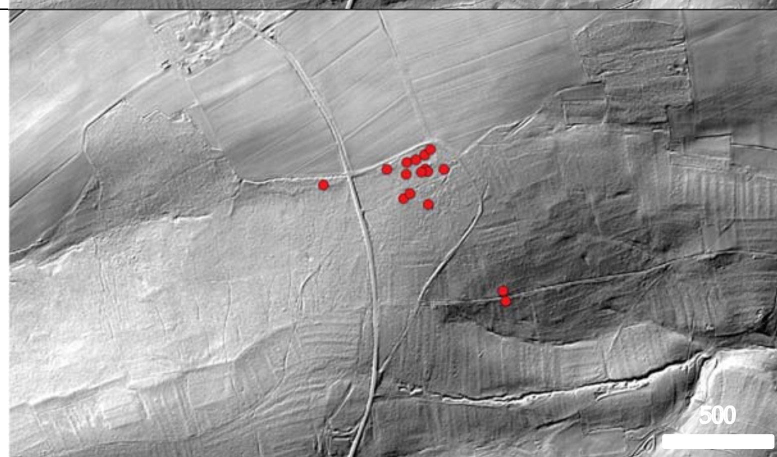
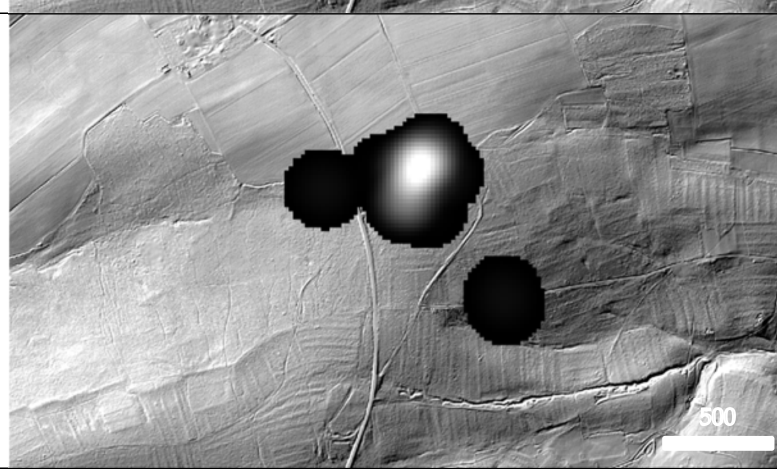
NAME	Riedenheim
Description	Burial mounds; one cluster
Temporal or cultural frame	Unknown prehistory
Ground truth estimate	11
Nearest administrative UID	202035
File number	D-6-6425-0062
Sub district	774;768

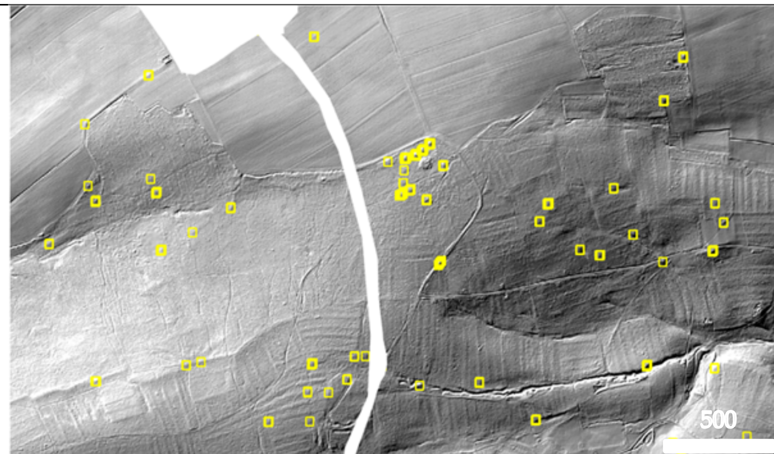
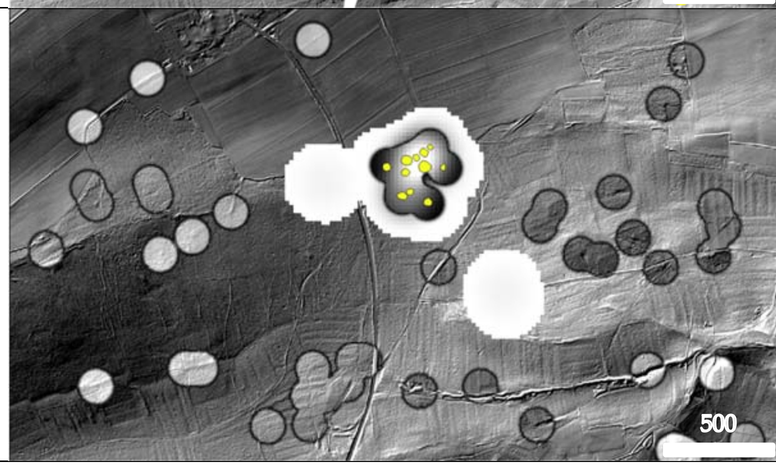
Description:

Burial mounds of various degree of destruction and deteriation. However, most of them seem undisturbed from looting. There are two spatial placements of burial mounds at the site within two clusters. The first cluster is situated along the northern ridge of the forest. The second cluster is a little further inside the forest. In between the clusters is an empty area devoid of mounds, but with a hollow road passing through. The road is of modern use, but likely extends back in time as primary road in the area.

Visual detection

Raw relief shade Sun zenith: 45 Sun azimuth: 315	
Burial cemetery recorded on site	

Burial mounds confirmed by field inspection	
Survey results of manual visual detection	
Survey results for visual detection by kernel density. Radius 100, Cellsize: 10 Weight: count Gradient: black to white from less to more	

COEFF_N Threshold val: 0.65 Template: 	
Verified BM Template pattern Gradient by Crowd-source pattern	

BM72 C1 View: NE Note: Dense vegetation over BM GK4: 4351290/ 5491630 [6275]	
BM74 C1 View: E Note: Flat topped BM with one of the only looting cuts in the area GK4: 4351333/ 5491647 [6280]	

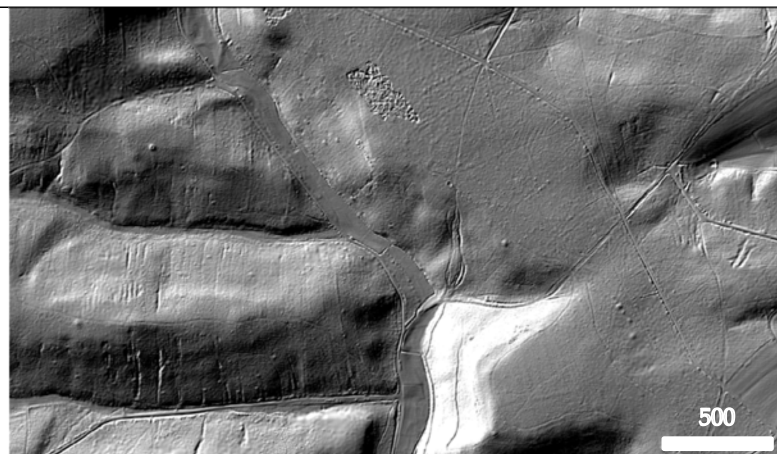
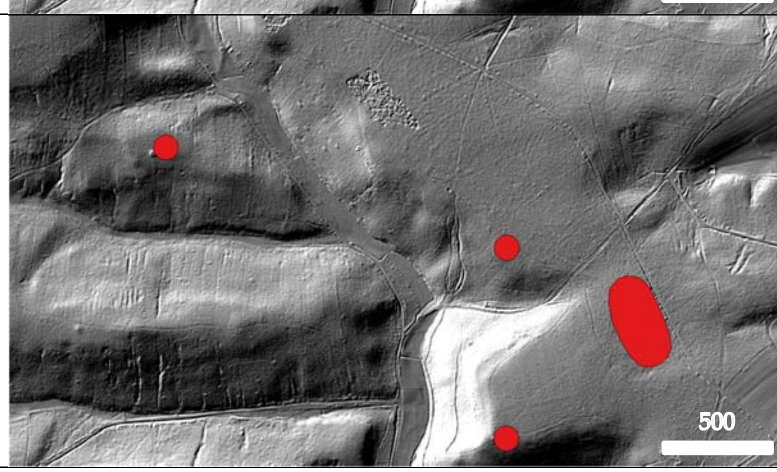
BM75 C1 View: N Note: Larger BM completely hollowed out by animal activity GK4: 4351334/ 5491614 [6293]	
BM78 C2 View: SW Note: Two separated BMs GK4: 4351280/ 5491541 [6295]	

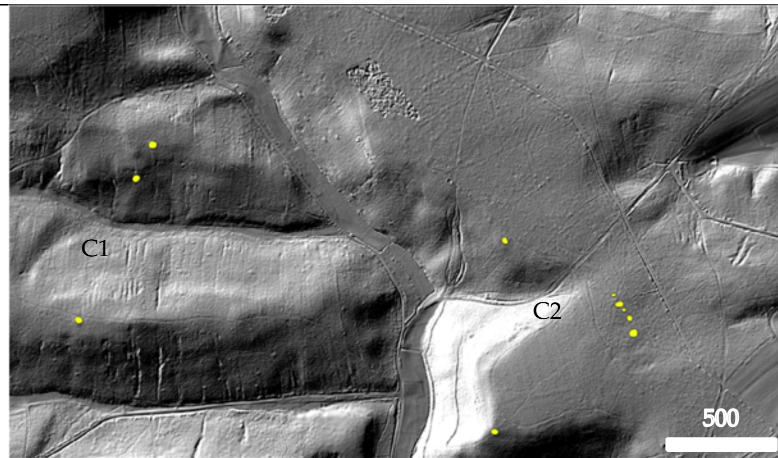
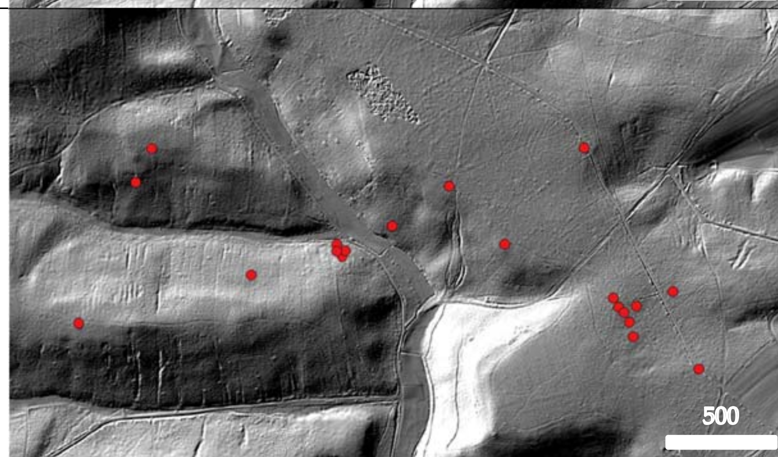
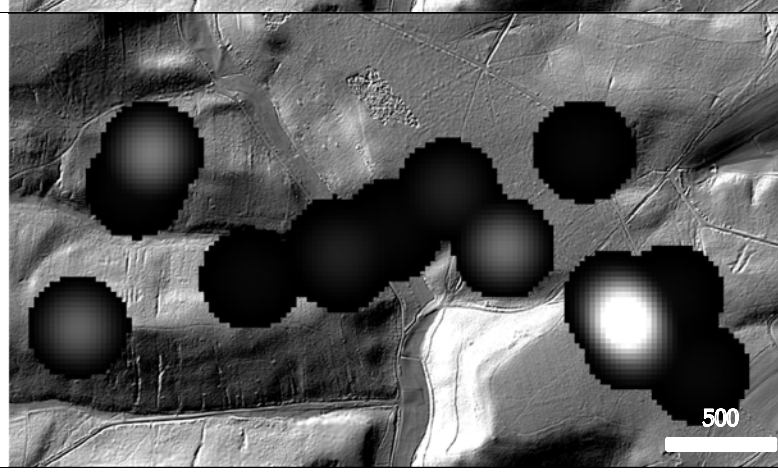
NAME	**Maroldsweisach**
Description	Burial mounds; two clusters
Temporal or cultural frame	Unknown prehistory
Ground truth estimate	10
Nearest administrative UID	134142; 132787; 132795; 132783
File number	D-6-5829-0008;D-6-5829-0012-4
Sub district	2138; 2138;2223

Description:

Dispersed pattern of individual and clustered groups of burial mounds on the slopes and plateaus of the landscape. In C1, one burial mound has since the LIDAR scanning been removed, and is no longer possible to locate in the field. The two others still present were large flat topped burial mounds. From C2 a dispersed pattern of burial mounds are seen. From the field investigation, the cluster of burial mounds were clear, and the two outer mounds also very likely prehistoric.

Visual detection

Raw relief shade Sun zenith: 45 Sun azimuth: 315	
Burial cemetery recorded on site	

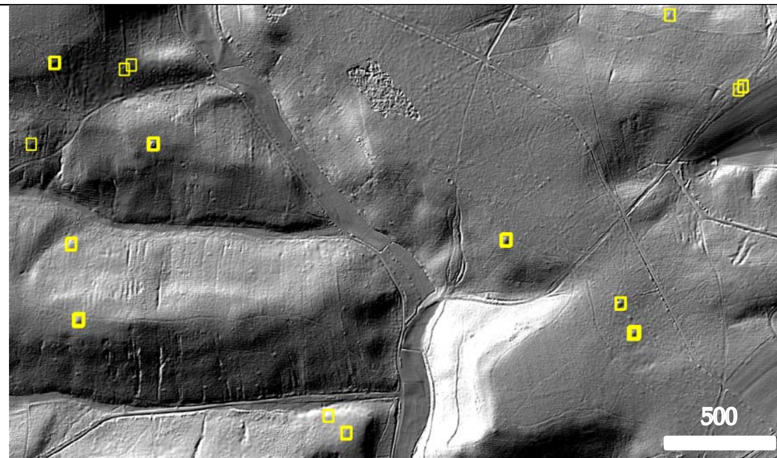
Burial mounds confirmed by field inspection	
Survey results of manual visual detection	
Survey results for visual detection by kernel density. Radius 100, Cellsize: 10 Weight: count Gradient: black to white from less to more	

COEFF_N

Threshold val:

0.6

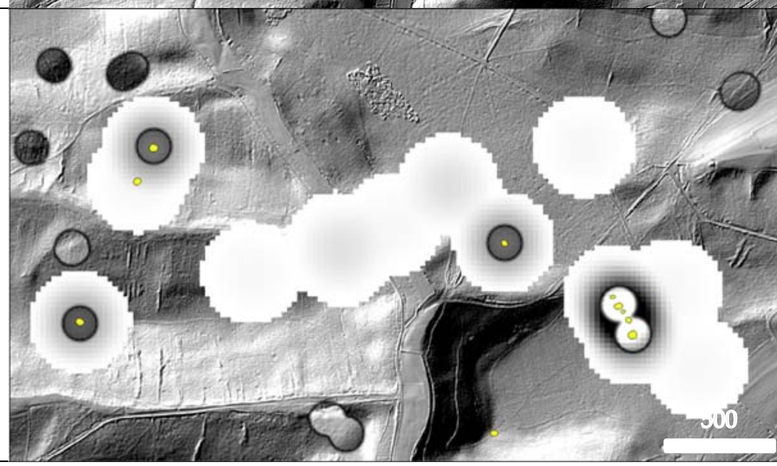
Template:



Verified BM

Template pattern

Gradient by Crowd-source pattern



BM110
C1
View: SE

Note:
Flat topped large BM

GK4:
4402693/
5561330

[6321]

<table>
<tr><td>BM120
C1
View: S

Note:
Area of missing BM

GK4:
4402836/
5561670

[6325]</td><td></td><td></td></tr>
<tr><td>BM111
C1
View: NW

Note:
Visible BM in the field, but almost invisible in the DTM

GK4:
4402804/
5561604

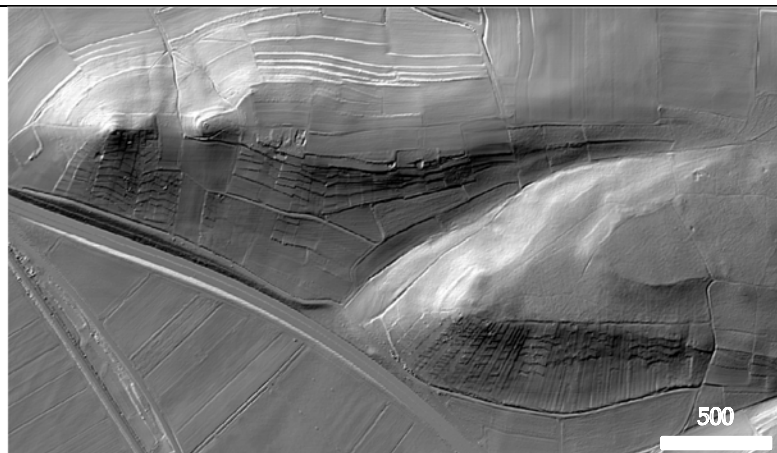
[6328]</td><td></td><td></td></tr>
</table>

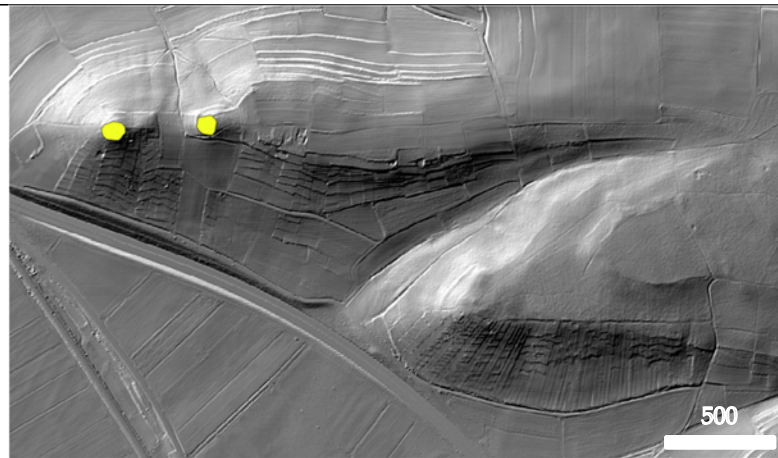
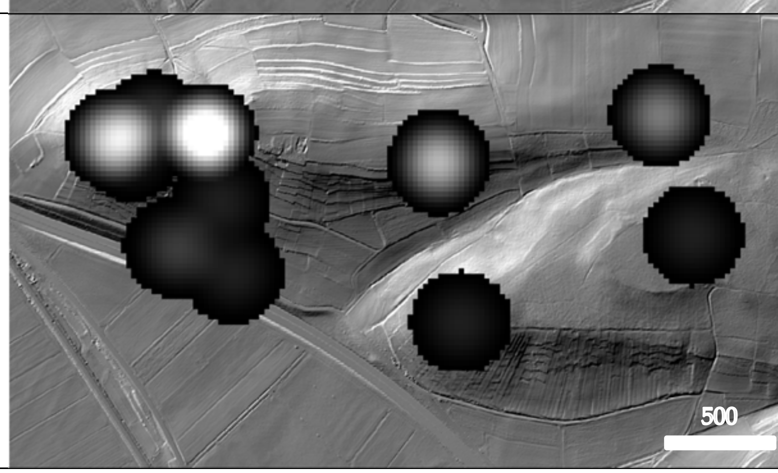
NAME	Stettfeld
Description	Burial mounds; one cluster
Temporal or cultural frame	Unknown prehistory
Ground truth estimate	2
Nearest administrative UID	181267; 134234
File number	D-4-6030-0023; D-6-6030-0005
Sub district	994;2291

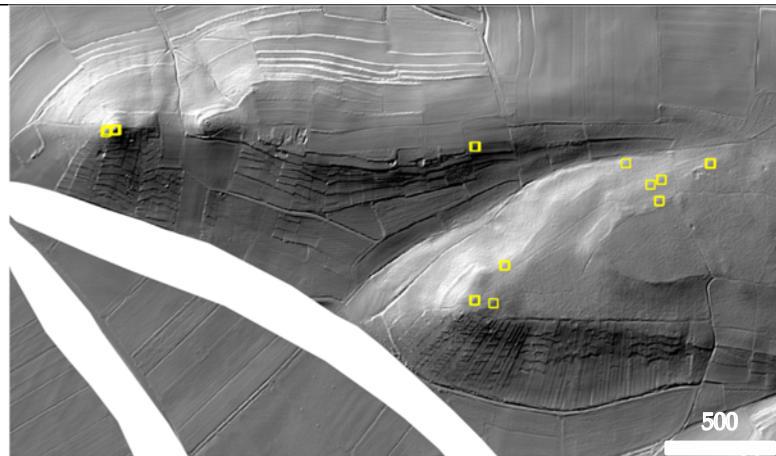
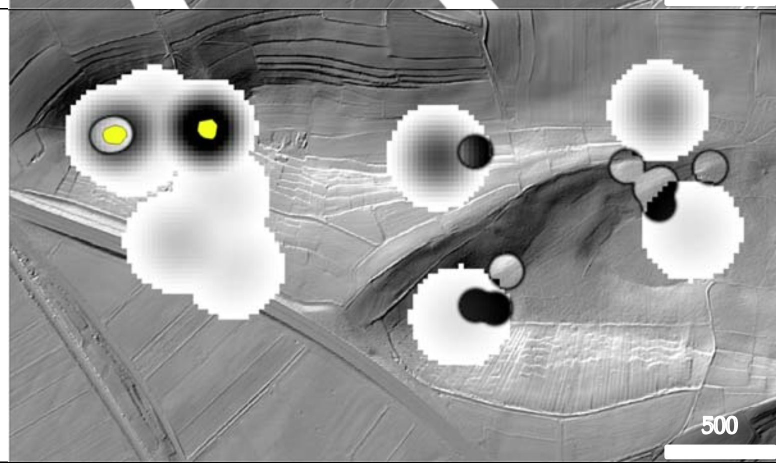
Description:

Two very centrally placed burial mounds on top of natural elevation. Both peaks of the Spitzlberg, have been in use for different purposes throughout time, and have been heavily shaped and destroyed by human activity. The western burial mound has been re-used as a new sarcophagus religious display, whereas the eastern mound has almost been completely hollowed out. Both burial mounds are therefore almost completely destroyed, but can still be recognised by their continued physical presence in landscape.

Visual detection

Raw relief shade Sun zenith: 45 Sun azimuth: 315	
Burial cemetery recorded on site	

Burial mounds confirmed by field inspection	
Survey results of manual visual detection	
Survey results for visual detection by kernel density. Radius 100, Cellsize: 10 Weight: count Gradient: black to white from less to more	

COEFF_N Threshold val: 0.87 Template: 	
Verified BM Template pattern Gradient by Crowd-source pattern	

BM130 C1 View: W Note: The extent of the unnatural hilltop GK4: 4409411/ 5536904 [6313]	
BM130 C1 View: N Note: Present day religious display GK4: 4409411/ 5536904 [6312]	

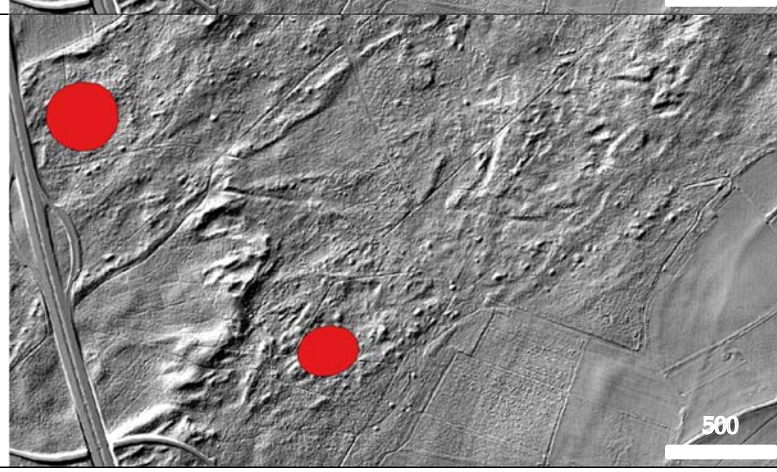
BM130 C1 View: E Note: Present day religious display GK4: 4409411/ 5536904 [6310]	
BM131 C1 View: W Note: The last remains of the burial mound after looting and destruction GK4: 4409595/ 5536912 [6318]	

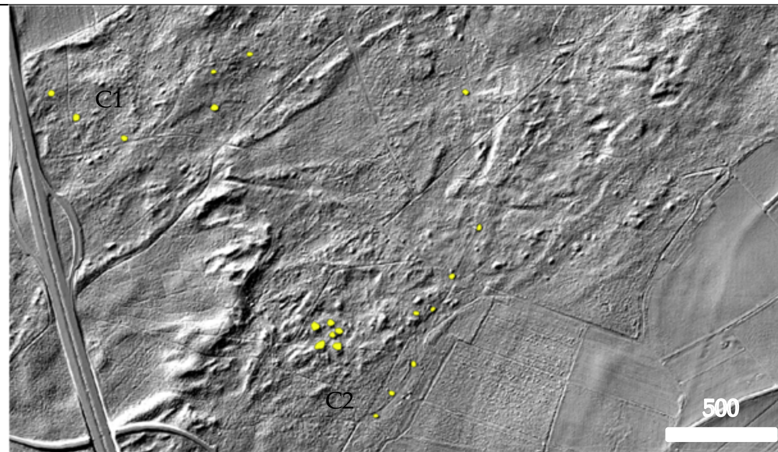
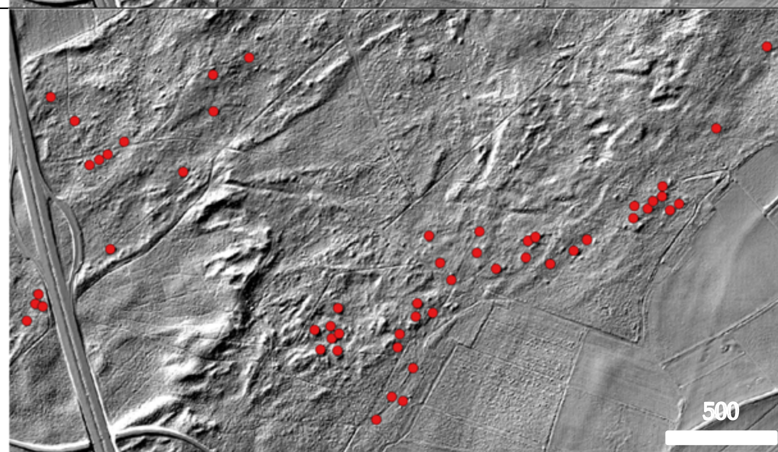
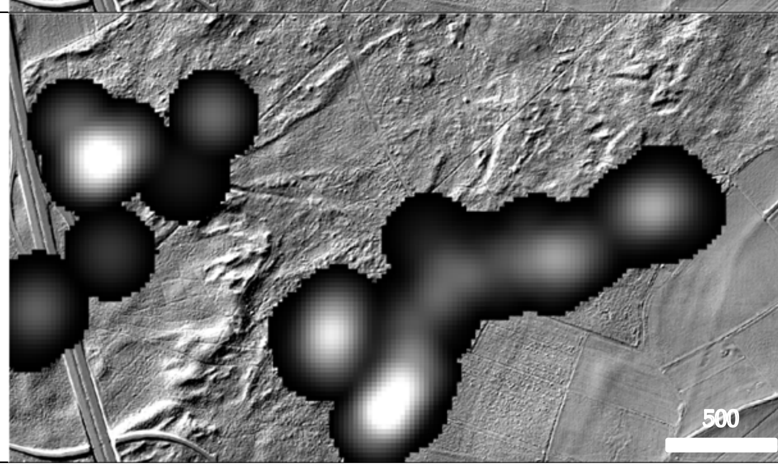
NAME	Alzenau
Description	Burial mounds; two clusters
Temporal or cultural frame	Unknown prehistory
Ground truth estimate	20
Nearest administrative UID	194524; 196034
File number	D-6-5920-0007; D-6-5920-0021
Sub district	994;2291

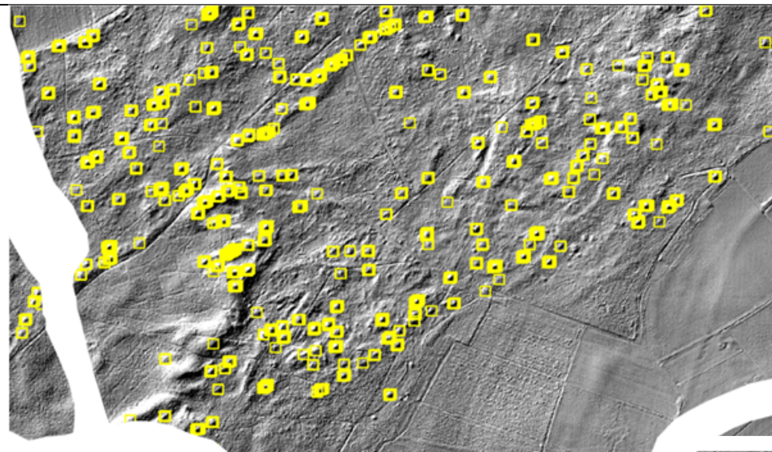
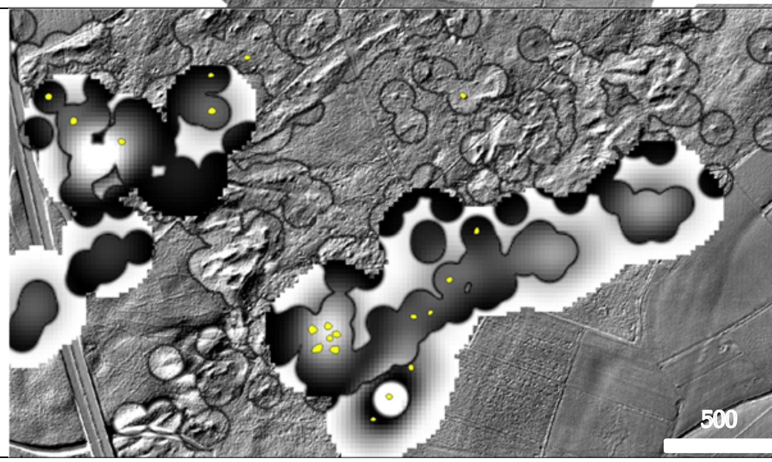
Description:

The two clusters of burial mounds at Alzenau are situated in an area of former migrating sand dunes, now held down by forest and canopies. However, this highly complicates the identification of burial mounds in the area. Undoubtedly there are two clusters of burial mounds in the area, but to determine their extent is extremely difficult by remote investigation, as well as by field investigation. Therefore the finale estimate is a very rough estimate, and the southern cluster, C2, seems to be the most prominent of the two.

Visual detection

Raw relief shade Sun zenith: 45 Sun azimuth: 315	
Burial cemetery recorded on site	

Burial mounds confirmed by field inspection	
Survey results of manual visual detection	
Survey results for visual detection by kernel density. Radius 100, Cellsize: 10 Weight: count Gradient: black to white from less to more	

COEFF_N Threshold val: 0.6 Template: 	
Verified BM Template pattern Gradient by Crowd-source pattern	

BM146 C1 View: SE Note: BM slightly cut by forest pathway GK4: 4288706/ 5551809 [6172]	
BM145 C1 View: E Note: BM slightly cut by forest pathway GK4: 4288742/ 5551805 [6173]	

<table>
<tr><td>BM143
C1
View: E

Note:
View from
BM145
towards
BM144
and
BM143

GK4:
4288742/
5551805

[6174]</td><td></td></tr>
<tr><td>BM154
C1
View: E

Note:
View from
BM154
and the
migrating
dune
landscape

GK4:
4288909/
5551874

[6174]</td><td></td></tr>
</table>

Appendix 4A

ID	Node label	reference
1	De Boer 2007	De Boer, A. 2007. Using Pattern Recognition to Search LIDAR Data for Archeological Sites. Proceedings of the 33rd Conference, Tomar, March 2005. CAA Portugal, Tomar, pp. 245-254.
2	Briese et al. 2009	Briese, C., Mandlburger, G. & Ressl, C., 2009. Automatic break line determination for the generation of a dtm along the river main. ISPRS, Vol. XXXIII, Part B3. Amsterdam 2000.
3	Hu & Ye 2013	Hu, X. and Ye, L. 2013. A fast and simple method of building detection from LiDAR data based on scan line analysis. ISPRS, Volume II-3/W1.
4	Karsli & Kahya 2008	Karsli, F. and Kahya, O., 2008. Building extraction from laser scanning data. ISPRS, Volume XXXVII Part B3b.
5	Mandlburger et al. 2010	Mandlburger, G., N. Pfeifer, C. Ressl, C. Briese, A. Roncat, H. Lehner & W. Muecke. 2010. Algorithms and tools for Airborne LiDAR data processing from a scientific perspective. European LiDAR Mapping Forum. The Hague, Netherlands.
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ID	Attribute_1	Attribute_2	Attribute_3	Auto_type	Year
1	ADC_Archeologisch Diensten Centrum	LiDAR	Cultural	Template	2007
2	University of Vienna	LiDAR	Technical	Attribute	2009
3	Wuhan University	LiDAR	Technical	Attribute	2013
4	Karadeniz Technical University	LiDAR	Technical	Attribute	2008
5	University of Vienna	LiDAR	Technical	Attribute	2010
6	University of Vienna	LiDAR	Technical	Attribute	2004
7	University of Twente	LiDAR	Technical	Attribute	2011
9	Norwegian Computing Center	LiDAR	Cultural	Template	2012
10	City University of New York	Aerial	Technical	Attribute	2010
11	Beijing Normal University	LiDAR	Technical	Attribute	2009
12	University of Leuven	Aerial	Cultural	Attribute	2007
13	University of Bamberg	Aerial	Cultural	Attribute	2012
14	Arizona State University	Aerial	Technical	Attribute	2011
15	University of Vienna	LiDAR	Technical	Attribute	2003
16	University of Oxford	Aerial	Technical	Attribute	1999
17	Ministry of Transport, Netherlands	LiDAR	Technical	Attribute	2000
18	University of Salzburg	LiDAR	Technical	Attribute	2014
19	University of Twente	LiDAR	Technical	Attribute	2009
20	Rovsing A/S	Aerial	Cultural	Template	2010
21	University of Maryland	Aerial	Technical	Attribute	2002
22	Monash University	Aerial	Technical	Attribute	2013
23	Technical University of Berlin	Aerial	Technical	Attribute	2012
24	University of Osnabrueck	LiDAR	Technical	Attribute	2009
25	National Central University	LiDAR	Technical	Attribute	2004
26	University of Heidelberg	Aerial	Cultural	Attribute	2007
27	Definiens Imaging GmbH_private	Aerial	Technical	Attribute	2004
28	University of Salzburg	Aerial	Technical	Attribute	2010
29	University of Winchester	Aerial	Cultural	Attribute	2014
30	National Research Council of Italy	Aerial	Cultural	Attribute	2014
31	University of East Anglia	Aerial	Cultural	Attribute	2006
32	National Research Council of Italy	Aerial	Cultural	Attribute	2012
33	Polytechnic University of Bari	Aerial	Cultural	Attribute	2014
34	University of Rome	Aerial	Cultural	Attribute	2010
35	Chinese Academy of Sciences	Aerial	Cultural	Attribute	2014
36	Brandenburg University of Technology	LiDAR	Cultural	Template	2015
37	University Columbus	Aerial	Cultural	Attribute	2013
38	University of Vienna	LiDAR	Cultural	Template	2014
39	Delft University of Technology	Aerial	Cultural	Attribute	1993
40	University of Vienna	LiDAR	Cultural	Both	2016
41	University of Konstanz	Aerial	Cultural	Attribute	2016
42	University of Leeds	LiDAR	Cultural	Attribute	2015

Appendix 4B

Node label	Node ID	Edge label	Edge ID	Year	Source	Target
De Boer 2007	1	Bradley 1985	101	1985	1	101
De Boer 2007	1	Brunelli & Poggio 1993	102	1993	1	102
De Boer 2007	1	Burrough & Mcdonnell 1998	103	1998	1	103
De Boer 2007	1	Fletcher & Lock 1984	104	1984	1	104
De Boer 2007	1	Fletcher & Spicer 1992	105	1992	1	105
De Boer 2007	1	Herzog 2001	106	2001	1	106
De Boer 2007	1	Laan & De Boer 2005	107	2005	1	107
De Boer 2007	1	Schmidt et al. 2005	108	2005	1	108
De Boer 2007	1	Sittler & Daeffler 2005	109	2005	1	109
De Boer 2007	1	Theodoridis & Koutroumbas 1999	110	1999	1	110
De Boer 2007	1	Theunissen 1999	111	1999	1	111
De Boer 2007	1	Van Zejverden & Laan 2004	112	2004	1	112
De Boer 2007	1	Waldus & Van der Velde 2005	113	2005	1	113
Briese et al. 2009	2	Axelsson 1999	114	1999	2	114
Briese et al. 2009	2	Briese 2004a	115	2004	2	115
Briese et al. 2009	2	Briese 2004b	116	2004	2	116
Briese et al. 2009	2	Briese & Pfeifer 2008	117	2008	2	117
Briese et al. 2009	2	Brügelmann 2000	118	2000	2	118
Briese et al. 2009	2	Doneus & Briese 2006	119	2006	2	119
Briese et al. 2009	2	Gomes-Pereira & Janssen 1999	120	1999	2	120
Briese et al. 2009	2	Gomes-Pereira & Wicherson 1999	121	1999	2	121
Briese et al. 2009	2	Kager 2004	122	2004	2	122
Briese et al. 2009	2	Karel et al. 2006	123	2006	2	123
Briese et al. 2009	2	Maas 2000	124	2000	2	124
Briese et al. 2009	2	Mandlburger & Briese 2007	125	2007	2	125
Briese et al. 2009	2	Mandlburger et al. 2008	126	2008	2	126
Briese et al. 2009	2	Ressl et al. 2008	127	2008	2	127
Briese et al. 2009	2	Ressl et al. 2009	128	2009	2	128
Briese et al. 2009	2	Sui 2002	129	2002	2	129
Hu & Ye 2013	3	Axelsson 1999	114	1999	3	114
Hu & Ye 2013	3	Axelsson 2000	131	2000	3	131
Hu & Ye 2013	3	Frédéricque et al. 2008	132	2008	3	132
Hu & Ye 2013	3	Douglas & Peucker 1973	133	1973	3	133
Hu & Ye 2013	3	Dorninger & Pfeifer 2008	134	2008	3	134
Hu & Ye 2013	3	Gross et al. 2005	135	2005	3	135
Hu & Ye 2013	3	Haithcoat et al. 2001	136	2001	3	136
Hu & Ye 2013	3	Hu et al. 2013	137	2013	3	137
Hu & Ye 2013	3	Kraus & Pfeifer 1998	138	1998	3	138
Hu & Ye 2013	3	Mayer 2008	139	2008	3	139
Hu & Ye 2013	3	Meng et al 2009	140	2009	3	140
Hu & Ye 2013	3	Moussa & El-Sheimy 2012	141	2012	3	141

Hu & Ye 2013	3	Rottensteiner et al 2012	142	2012	3	142
Hu & Ye 2013	3	Rutzinger et al. 2009	143	2009	3	143
Hu & Ye 2013	3	Sithole 2005	144	2005	3	144
Hu & Ye 2013	3	Sithole & Vosselman 2004	145	2004	3	145
Hu & Ye 2013	3	Tóvári & Pfeifer 2005	146	2005	3	146
Hu & Ye 2013	3	Vosselman 2000	147	2000	3	147
Hu & Ye 2013	3	Wu & Márquez 2003	148	2003	3	148
Hu & Ye 2013	3	Zhang & Lin 2012	149	2012	3	149
Hu & Ye 2013	3	Zhou & Neumann 2009	150	2009	3	150
Karsli & Kahya 2008	4	Atiquazzaman & Akhtar 1994	151	1994	4	151
Karsli & Kahya 2008	4	Atiquazzaman & Akhtar 1995	152	1995	4	152
Karsli & Kahya 2008	4	Davies 1988	153	1988	4	153
Karsli & Kahya 2008	4	Ballard 1981	154	1981	4	154
Karsli & Kahya 2008	4	Gonzales et al. 2004	155	2004	4	155
Karsli & Kahya 2008	4	Hough 1962	156	1962	4	156
Karsli & Kahya 2008	4	Maas & Vosselman 1999	157	1999	4	157
Karsli & Kahya 2008	4	Nguyen et al. 2005	158	2005	4	158
Karsli & Kahya 2008	4	Oda et al. 2004	159	2004	4	159
Karsli & Kahya 2008	4	Overby et al. 2004	160	2004	4	160
Karsli & Kahya 2008	4	Rabbani et al. 2005	161	2005	4	161
Karsli & Kahya 2008	4	Richards & Casasent 1991	162	1991	4	162
Karsli & Kahya 2008	4	Rottensteiner 2003	163	2003	4	163
Karsli & Kahya 2008	4	Tarsha-Kurdi et al. 2007	164	2007	4	164
Karsli & Kahya 2008	4	Vosselman & Dijkman 2001	165	2001	4	165
Mandlburger et al. 2010	5	Briese 2004a	115	2004	5	115
Mandlburger et al. 2010	5	Briese et al. 2008	167	2008	5	167
Mandlburger et al. 2010	5	Chauve et al 2009	168	2009	5	168
Mandlburger et al. 2010	5	Doneus et al. 2008	169	2008	5	169
Mandlburger et al. 2010	5	Hoefle et al. 2009	24	2009	5	170
Mandlburger et al. 2010	5	Hofton 2000	171	2000	5	171
Mandlburger et al. 2010	5	Kager 2004	122	2004	5	122
Mandlburger et al. 2010	5	Kraus & Pfeifer 1998	138	1998	5	138
Mandlburger et al. 2010	5	Lehner & Briese 2010	174	2010	5	174
Mandlburger et al. 2010	5	Lin & Mills 2010	175	2009	5	175
Mandlburger et al. 2010	5	Mallet & Bretar 2009	176	2009	5	176
Mandlburger et al. 2010	5	Mandlburger et al. 2007	177	2007	5	177
Mandlburger et al. 2010	5	Mandlburger et al. 2009a	178	2009	5	178
Mandlburger et al. 2010	5	Mandlburger et al. 2009b	179	2009	5	179
Mandlburger et al. 2010	5	Mücke et al. 2010	180	2010	5	180
Mandlburger et al. 2010	5	Otepka et al. 2006	181	2006	5	181
Mandlburger et al. 2010	5	Pfeifer & Mandlburger 2008	182	2008	5	182
Mandlburger et al. 2010	5	Ressl et al. 2009	128	2009	5	128
Mandlburger et al. 2010	5	Roncat et al. 2010a	184	2010	5	184

Mandlburger et al. 2010	5	Roncat et al. 2010b	185	2010	5	185
Mandlburger et al. 2010	5	Skaloud 2007	186	2007	5	186
Mandlburger et al. 2010	5	Wagner 2010	187	2010	5	187
Mandlburger et al. 2010	5	Wagner et al. 2006	188	2006	5	188
Mandlburger et al. 2010	5	Yu et al. 2010	189	2010	5	189
Melzer & Briese 2004	6	Axelsson 1999	114	1999	6	114
Melzer & Briese 2004	6	Besl & Jain 1988	191	1988	6	191
Melzer & Briese 2004	6	Duda et al. 2000	192	2000	6	192
Melzer & Briese 2004	6	Gonzales & Wintz 1987	193	1987	6	193
Melzer & Briese 2004	6	Hartley & Zisserman 2000	194	2000	6	194
Melzer & Briese 2004	6	Hoover et al. 1996	195	1996	6	195
Melzer & Briese 2004	6	Kraus & Pfeifer 1998	138	1998	6	138
Melzer & Briese 2004	6	Martines & Schulten 1994	197	1994	6	197
Melzer & Briese 2004	6	Rottensteiner & Briese 2002	198	2002	6	198
Melzer & Briese 2004	6	Wagner et al. 2004	199	2004	6	199
Melzer & Briese 2004	6	Wehr & Lohr 1999	200	1999	6	200
Rutzinger et al. 2011	7	Anders et al. 2009	201	2009	7	201
Rutzinger et al. 2011	7	Asselen & Seijmonsbergen 2006	202	2006	7	202
Rutzinger et al. 2011	7	Benz et al. 2004	27	2004	7	203
Rutzinger et al. 2011	7	Bailly et al. 2008	204	2008	7	204
Rutzinger et al. 2011	7	Blaschke et al. 2008	205	2008	7	205
Rutzinger et al. 2011	7	Briese 2004b	116	2004	7	116
Rutzinger et al. 2011	7	Briese 2010	207	2010	7	207
Rutzinger et al. 2011	7	Brügelmann 2000	118	2000	7	118
Rutzinger et al. 2011	7	Brzank et al. 2008	209	2008	7	209
Rutzinger et al. 2011	7	Clark & Wilson 1994	210	1994	7	210
Rutzinger et al. 2011	7	Geist et al. 2009	211	2009	7	211
Rutzinger et al. 2011	7	Glenn et al. 2006	212	2006	7	212
Rutzinger et al. 2011	7	Gruber 2004	213	2004	7	213
Rutzinger et al. 2011	7	Hoefle & Rutzinger 2011	214	2011	7	214
Rutzinger et al. 2011	7	Jordan & Schott 2005	215	2005	7	215
Rutzinger et al. 2011	7	Kraus & Pfeifer 1998	138	1998	7	138
Rutzinger et al. 2011	7	Mavrantza & Argialas 2008	217	2008	7	217
Rutzinger et al. 2011	7	McKean & Goering 2004	218	2004	7	218
Rutzinger et al. 2011	7	Nyborg et al. 2007	219	2007	7	219
Rutzinger et al. 2011	7	Pfeifer & Mandlburger 2009	220	2009	7	220
Rutzinger et al. 2011	7	Rutzinger et al. 2007	221	2007	7	221
Rutzinger et al. 2011	7	Shan & Toth 2009	222	2009	7	222
Rutzinger et al. 2011	7	Sithole & Vosselman 2004	145	2004	7	145
Rutzinger et al. 2011	7	Vosselman & Liang 2009	224	2009	7	224
Rutzinger et al. 2011	7	Vosselman & Maas 2010	225	2010	7	225
Rutzinger et al. 2011	7	Wladis 1999	226	1999	7	226
Rutzinger et al. 2011	7	Wood 1996	227	1996	7	227

Trier & Zortea 2012	9	Aurdal et al. 2006	243	2006	9	243
Trier & Zortea 2012	9	Devereux et al. 2005	244	2005	9	244
Trier & Zortea 2012	9	Hastie et al. 2009	245	2009	9	245
Trier & Zortea 2012	9	Prokop & Reeves 1992	246	1992	9	246
Trier & Zortea 2012	9	Pudil et al. 1994	247	1994	9	247
Trier & Zortea 2012	9	Trier et al. 2009	248	2009	9	248
Trier & Zortea 2012	9	Trier & Piloe 2012	249	2012	9	249
Bhaskaran et al. 2010	10	Anderson 1971	250	1971	10	250
Bhaskaran et al. 2010	10	Baatz & Schape 2000	251	2000	10	251
Bhaskaran et al. 2010	10	Benz et al. 2004	27	2004	10	203
Bhaskaran et al. 2010	10	Bhaskaran 2004	253	2004	10	253
Bhaskaran et al. 2010	10	Blaschke & Strobl 2001	254	2001	10	254
Bhaskaran et al. 2010	10	Bolstad & Lillesand 1991	255	1991	10	255
Bhaskaran et al. 2010	10	Casals-Carrasco et al. 2000	256	2000	10	256
Bhaskaran et al. 2010	10	Clark & Jantz 1995	257	1995	10	257
Bhaskaran et al. 2010	10	Congalton & Green 1999	258	1999	10	258
Bhaskaran et al. 2010	10	Cowen & Jensen 1998	259	1998	10	259
Bhaskaran et al. 2010	10	Dare 2005	260	2005	10	260
Bhaskaran et al. 2010	10	Dean & Smith 2003	261	2003	10	261
Bhaskaran et al. 2010	10	Dial et al. 2003	262	2003	10	262
Bhaskaran et al. 2010	10	Forster 1983	263	1983	10	263
Bhaskaran et al. 2010	10	Gatrell & Jensen 2008	264	2008	10	264
Bhaskaran et al. 2010	10	Gitas et al. 2004	265	2004	10	265
Bhaskaran et al. 2010	10	Goetz et al. 2003	266	2003	10	266
Bhaskaran et al. 2010	10	Hardin et al. 2007	267	2007	10	267
Bhaskaran et al. 2010	10	Hellden 1980	268	1980	10	268
Bhaskaran et al. 2010	10	Herold et al. 2003	269	2003	10	269
Bhaskaran et al. 2010	10	Herold & Scepan 2002	270	2002	10	270
Bhaskaran et al. 2010	10	Hofmann 2001	271	2001	10	271
Bhaskaran et al. 2010	10	Ippoliti-Ramilo et al. 2003	272	2003	10	272
Bhaskaran et al. 2010	10	Ivits & Koch 2002	273	2002	10	273
Bhaskaran et al. 2010	10	Jat et al. 2008	274	2008	10	274
Bhaskaran et al. 2010	10	Jensen & Cowen 1999	275	1999	10	275
Bhaskaran et al. 2010	10	Jensen & Im 2007	276	2007	10	276
Bhaskaran et al. 2010	10	Kato & Yamaguchi 2005	277	2005	10	277
Bhaskaran et al. 2010	10	Kim & Madden 2009	278	2009	10	278
Bhaskaran et al. 2010	10	Lillesand & Kiefer 1994	279	1994	10	279
Bhaskaran et al. 2010	10	Lo & Choi 2004	280	2004	10	280
Bhaskaran et al. 2010	10	Longley et al. 2001	281	2001	10	281
Bhaskaran et al. 2010	10	Lucieer et al. 2005	282	2005	10	282
Bhaskaran et al. 2010	10	Madhavan et al. 2001	283	2001	10	283
Bhaskaran et al. 2010	10	Mather 1987	284	1987	10	284
Bhaskaran et al. 2010	10	Pizzolato & Haertel 2003	285	2003	10	285

Bhaskaran et al. 2010	10	Richards 1999	286	1999	10	286
Bhaskaran et al. 2010	10	Richards & Jia 1999	287	1999	10	287
Bhaskaran et al. 2010	10	Sanchez 2004	288	2004	10	288
Bhaskaran et al. 2010	10	Sawaya et al. 2003	289	2003	10	289
Bhaskaran et al. 2010	10	Shackelford & Davis 2003	290	2003	10	290
Bhaskaran et al. 2010	10	Shalaby & Tateishi 2007	291	2007	10	291
Bhaskaran et al. 2010	10	Shettigara 1991	292	1991	10	292
Bhaskaran et al. 2010	10	Short 1982	293	1982	10	293
Bhaskaran et al. 2010	10	Stow et al. 2007	294	2007	10	294
Bhaskaran et al. 2010	10	Tapiador & Casanova 2003	295	2003	10	295
Bhaskaran et al. 2010	10	Thapa & Murayama 2009	296	2009	10	296
Bhaskaran et al. 2010	10	Thomas et al. 1987	297	1987	10	297
Bhaskaran et al. 2010	10	Walker & Blaschke 2008	298	2008	10	298
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Bhaskaran et al. 2010	10	Yu et al. 2006	304	2006	10	304
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Bhaskaran et al. 2010	10	Yuan & Bauer 2006	306	2006	10	306
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Bhaskaran et al. 2010	10	Zhou & Robson 2001	310	2001	10	310
Bhaskaran et al. 2010	10	Zhou & Troy 2008	311	2008	10	311
Chen et al. 2009	11	Aplin 1999	312	1999	11	312
Chen et al. 2009	11	Baatz & Schape 2000	251	2000	11	251
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Chen et al. 2009	11	Campbell 1987	316	1987	11	316
Chen et al. 2009	11	Chang & Li 1994	317	1994	11	317
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Chen et al. 2009	11	Acqua 2001	321	2001	11	321
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Chen et al. 2009	11	Haala & Brenner 1999	328	1999	11	328

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Rottensteiner 2003	15	Brenner 2000	445	2000	15	445
Rottensteiner 2003	15	Vosselman & Dijkman 2001	165	2001	15	165
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Brügelmann 2000	17	Gomes-Pereira & Janssen 1999	120	1999	17	120
Brügelmann 2000	17	Gomes-Pereira & Wicherson 1999	121	1999	17	121
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Awrangjeb & Fraser 2013	22	Awrangjeb & Lu 2008	606	2008	22	606
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Awrangjeb & Fraser 2013	22	Dorninger & Pfeifer 2008	134	2008	22	134
Awrangjeb & Fraser 2013	22	Haala & Kada 2010	614	2010	22	614
Awrangjeb & Fraser 2013	22	Jochem et al. 2012	526	2012	22	526
Awrangjeb & Fraser 2013	22	Khoshelham et al. 2005	616	2005	22	616
Awrangjeb & Fraser 2013	22	Kim & Shan 2011	617	2011	22	617
Awrangjeb & Fraser 2013	22	Lafarge et al. 2010	618	2010	22	618
Awrangjeb & Fraser 2013	22	Perera et al. 2012	619	2012	22	619
Awrangjeb & Fraser 2013	22	Rottensteiner 2003	163	2003	22	163
Awrangjeb & Fraser 2013	22	Rottensteiner 2007	621	2007	22	621
Awrangjeb & Fraser 2013	22	Rottensteiner & Briese 2003	335	2003	22	335
Awrangjeb & Fraser 2013	22	Rottensteiner et al. 2012	623	2012	22	623
Awrangjeb & Fraser 2013	22	Rutzinger et al. 2009	143	2009	22	143
Awrangjeb & Fraser 2013	22	Sampath & Shan 2010	625	2010	22	625
Awrangjeb & Fraser 2013	22	Satari et al 2012	626	2012	22	626
Awrangjeb & Fraser 2013	22	Sohn et al 2008	627	2008	22	627
Awrangjeb & Fraser 2013	22	Tarsha-Kurdi et al. 2008	628	2008	22	628
Awrangjeb & Fraser 2013	22	Verna et al. 2006	629	2006	22	629

Awrangjeb & Fraser 2013	22	Vosselman et al. 2004	242	2004	22	242
Awrangjeb & Fraser 2013	22	Zhang et al. 2005a	631	2005	22	631
D'Hondt et al. 2012	23	Reigber & Moreira 2000	632	2000	23	632
D'Hondt et al. 2012	23	Guillaso & Reigber 2005	633	2005	23	633
D'Hondt et al. 2012	23	Zhu & Bamler 2012	634	2012	23	634
D'Hondt et al. 2012	23	Guillaso et al. 2012	635	2012	23	635
D'Hondt et al. 2012	23	Fischler & Bolles 1981	572	1981	23	572
D'Hondt et al. 2012	23	Bughin et al. 2010	637	2010	23	637
D'Hondt et al. 2012	23	Chum et al. 2003	638	2003	23	638
D'Hondt et al. 2012	23	Toldo & Fusiello 2008	639	2008	23	639
D'Hondt et al. 2012	23	Torr & Murray 1994	640	1994	23	640
Hoefle et al. 2009	24	Dorninger & Pfeifer 2008	134	2008	24	134
Hoefle et al. 2009	24	Filin & Pfeifer 2006	642	2006	24	642
Hoefle et al. 2009	24	Hoefle et al. 2006	643	2006	24	643
Hoefle et al. 2009	24	Hoefle et al. 2008	644	2008	24	644
Hoefle et al. 2009	24	Kaartinen et al. 2005	645	2005	24	645
Hoefle et al. 2009	24	Maas & Vosselman 1999	157	1999	24	157
Hoefle et al. 2009	24	Melzer 2007	647	2007	24	647
Hoefle et al. 2009	24	Nothegger & Dorninger 2009	648	2009	24	648
Hoefle et al. 2009	24	Pfeifer et al. 2001	649	2001	24	649
Hoefle et al. 2009	24	Rutzinger et al. 2008	650	2008	24	650
Hoefle et al. 2009	24	Rutzinger et al. 2009	143	2009	24	143
Teo & Chen 2004	25	Behan 2000	652	2000	25	652
Teo & Chen 2004	25	Briese et al. 2002	653	2000	25	653
Teo & Chen 2004	25	Fraser & Hanley 2003	654	2003	25	654
Teo & Chen 2004	25	Halla & Walter 1999	655	1999	25	655
Teo & Chen 2004	25	Hofmann & Van der Vegt 2001	656	2001	25	656
Teo & Chen 2004	25	Hofmann et al. 2002	522	2002	25	522
Teo & Chen 2004	25	Lohmann 2002	658	2002	25	658
Teo & Chen 2004	25	Maas 1999	659	1999	25	659
Teo & Chen 2004	25	Nakagawa et al. 2002	660	2002	25	660
Teo & Chen 2004	25	Rottensteiner & Jansa 2002	661	2002	25	661
Teo & Chen 2004	25	Schiewe 2003	662	2003	25	662
Teo & Chen 2004	25	Vosselman 2002	348	2002	25	348
Teo & Chen 2004	25	Walter 2004	664	2004	25	664
Teo & Chen 2004	25	Zhang 1999	665	1999	25	665
Teo & Chen 2004	25	Zeng et al. 2002	666	2002	25	666
Menze et al. 2007a	26	Adams 1972	667	1972	26	667
Menze et al. 2007a	26	Adams & Nissen 1972	668	1972	26	668
Menze et al. 2007a	26	Altaweel 2003	669	2003	26	669
Menze et al. 2007a	26	Altaweel 2004	670	2004	26	670
Menze et al. 2007a	26	Altaweel 2005	671	2005	26	671
Menze et al. 2007a	26	Andrae 1977	672	1977	26	672

Menze et al. 2007a	26	Bagg 2000	673	2000	26	673
Menze et al. 2007a	26	Brandt et al. 1992	674	1992	26	674
Menze et al. 2007a	26	Dittmann 1995	675	1995	26	675
Menze et al. 2007a	26	El-Amin & Mallowan 1949	676	1949	26	676
Menze et al. 2007a	26	El-Amin & Mallowan 1950	677	1950	26	677
Menze et al. 2007a	26	Fowler 2002	678	2002	26	678
Menze et al. 2007a	26	Gabaix & Ioannides 2003	679	2003	26	679
Menze et al. 2007a	26	Gheyle et al. 2004	680	2004	26	680
Menze et al. 2007a	26	Kessler 1997	681	1997	26	681
Menze et al. 2007a	26	Hritz & Wilkinson 1996	682	1996	26	682
Menze et al. 2007a	26	Hours et al. 1994	683	1994	26	683
Menze et al. 2007a	26	Lawler 2006	684	2006	26	684
Menze et al. 2007a	26	Lehmann 2002	685	2002	26	685
Menze et al. 2007a	26	Manrubia & Zanette 1998	686	1998	26	686
Menze et al. 2007a	26	Mehrer & Wescott 2006	687	2006	26	687
Menze et al. 2007a	26	Menze 2005	688	2005	26	688
Menze et al. 2007a	26	Menze et al. 2007b	689	2007	26	689
Menze et al. 2007a	26	Menze et al. 2006	690	2006	26	690
Menze et al. 2007a	26	Nitsch 2005	691	2005	26	691
Menze et al. 2007a	26	Rosenstock 2005	692	2005	26	692
Menze et al. 2007a	26	Sarre 1911	693	1911	26	693
Menze et al. 2007a	26	Scollar et al. 1990	694	1990	26	694
Menze et al. 2007a	26	Schroeder 1820	695	1820	26	695
Menze et al. 2007a	26	Sherratt 2004	696	2004	26	696
Menze et al. 2007a	26	Ur 2002	697	2002	26	697
Menze et al. 2007a	26	Ur 2003	698	2003	26	698
Menze et al. 2007a	26	Ur 2004	699	2004	26	699
Menze et al. 2007a	26	Van Lierre & Lauffray 1955	700	1955	26	700
Menze et al. 2007a	26	Weiss 1986	701	1986	26	701
Menze et al. 2007a	26	Wilkinson 1993	702	1993	26	702
Menze et al. 2007a	26	Wilkinson & Tucker 1995	703	1995	26	703
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Menze et al. 2007a	26	Wilkinson et al. 2005	706	2005	26	706
Menze et al. 2007a	26	Wirth 1962	707	1962	26	707
Benz et al. 2004	27	Baatz & Mimler 2002	708	2002	27	708
Benz et al. 2004	27	Baatz & Schape 2000	251	2000	27	251
Benz et al. 2004	27	Bandemer & Gottwald 1995	710	1995	27	710
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Benz et al. 2004	27	Bezdek & Pal 1992	712	1992	27	712
Benz et al. 2004	27	Civanlar & Trussel 1986	713	1986	27	713
Benz et al. 2004	27	Coulde & Pottier 1996	714	1996	27	714
Benz et al. 2004	27	Curlander & Kober 1992	715	1992	27	715

Benz et al. 2004	27	Daida et al. 1990	716	1990	27	716
Benz et al. 2004	27	Douglas & Peucker 1973	133	1973	27	133
Benz et al. 2004	27	Ghassemian & Landgrebe 1988	718	1988	27	718
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Bennett et al. 2014	29	Hanson 2010	936	2010	29	936
Bennett et al. 2014	29	Hill 2009	937	2009	29	937
Bennett et al. 2014	29	Horne 2009	938	2009	29	938
Bennett et al. 2014	29	De laet et al. 2007	12	2007	29	12
Bennett et al. 2014	29	Lambers & Zingman 2013	13	2013	29	13
Bennett et al. 2014	29	Lasaponara & Masini 2012a	388	2012	29	388
Bennett et al. 2014	29	Palmer 2011	942	2011	29	942
Bennett et al. 2014	29	Parcak 2009	392	2009	29	392
Bennett et al. 2014	29	Pascal & Pascal 2013	944	2013	29	944
Bennett et al. 2014	29	Risboel et al. 2013	945	2013	29	945
Bennett et al. 2014	29	Sonka et al. 2008	946	2008	29	946
Bennett et al. 2014	29	Trier & Piloe 2012	249	2012	29	249
Bennett et al. 2014	29	Trier et al. 2009	248	2009	29	248
Bennett et al. 2014	29	Verhagen & Dragut 2012	949	2012	29	949
Bennett et al. 2014	29	Verhoeven 2012	950	2012	29	950
Bennett et al. 2014	29	Wilson 2000	951	2000	29	951
Lasaponara et al. 2014	30	Alva 2001	952	2001	30	952
Lasaponara et al. 2014	30	Anselin 1995	953	1995	30	953
Lasaponara et al. 2014	30	Atwood 2006	954	2006	30	954
Lasaponara et al. 2014	30	Ball & Hall 1965	955	1965	30	955
Lasaponara et al. 2014	30	Brodie et al. 2001	956	2001	30	956
Lasaponara et al. 2014	30	Brodie & Renfrew 2005	957	2005	30	957
Lasaponara et al. 2014	30	Cliff & Ord 1981	958	1981	30	958
Lasaponara et al. 2014	30	Contreras 2010	959	2010	30	959
Lasaponara et al. 2014	30	Conyers & Goodman 1997	960	1997	30	960
Lasaponara et al. 2014	30	Conyers 2004	961	2004	30	961
Lasaponara et al. 2014	30	Conyers 2006	962	2006	30	962
Lasaponara et al. 2014	30	Conyers 2012	963	2012	30	963
Lasaponara et al. 2014	30	Conyers et al. 2013	964	2013	30	964
Lasaponara et al. 2014	30	Daniels et al. 1988	965	1988	30	965
Lasaponara et al. 2014	30	Davis & Annan 1989	966	1989	30	966
Lasaponara et al. 2014	30	Fotheringham et al. 2002	967	2002	30	967
Lasaponara et al. 2014	30	Geary 1954	968	1954	30	968
Lasaponara et al. 2014	30	Getis & Ord 1994	969	1994	30	969
Lasaponara et al. 2014	30	Goodman 2013	970	2013	30	970
Lasaponara et al. 2014	30	Goodman et al. 2006	971	2006	30	971
Lasaponara et al. 2014	30	Goodman & Piro 2013	972	2013	30	972
Lasaponara et al. 2014	30	Hearn 2007	973	2007	30	973

Lasaponara et al. 2014	30	Illian et al. 2008	974	2008	30	974
Lasaponara et al. 2014	30	Laben et al. 2000	975	2000	30	975
Lasaponara et al. 2014	30	Lasaponara & Masini 2010	976	2010	30	976
Lasaponara et al. 2014	30	Lasaponara et al. 2011a	977	2011	30	977
Lasaponara et al. 2014	30	Lasaponara & Masini 2012c	978	2012	30	978
Lasaponara et al. 2014	30	Lasaponara et al. 2012b	979	2012	30	979
Lasaponara et al. 2014	30	Leucci 2012	980	2012	30	980
Lasaponara et al. 2014	30	MacQueen 1967	981	1967	30	981
Lasaponara et al. 2014	30	Masini et al. 2012	982	2012	30	982
Lasaponara et al. 2014	30	Moran 1948	983	1948	30	983
Lasaponara et al. 2014	30	Parcak 2007	984	2007	30	984
Lasaponara et al. 2014	30	Reynolds 1998	985	1998	30	985
Lasaponara et al. 2014	30	Sandmeier 2011	986	2011	30	986
Lasaponara et al. 2014	30	Sheriff & Geldart 1995	987	1995	30	987
Lasaponara et al. 2014	30	Silverman 1993	988	1993	30	988
Lasaponara et al. 2014	30	Smith 2005	989	2005	30	989
Lasaponara et al. 2014	30	Stone 2008	990	2008	30	990
Lasaponara et al. 2014	30	Van Ess et al. 2006	991	2006	30	991
Lasaponara et al. 2014	30	Watson 1999	992	1999	30	992
Lasaponara et al. 2014	30	Widess 1973	993	1973	30	993
Lasaponara et al. 2014	30	Woodward et al. 2003	994	2003	30	994
Lasaponara et al. 2014	30	Yilmaz 1987	995	1987	30	995
Bescoby 2006	31	Alcock 1993	996	1993	31	996
Bescoby 2006	31	Ballester 1996	997	1996	31	997
Bescoby 2006	31	Bescoby 2007	998	2007	31	998
Bescoby 2006	31	Bescoby et al. 2004	999	2004	31	999
Bescoby 2006	31	Bracewell 1995	1000	1995	31	1000
Bescoby 2006	31	Casas et al. 2000	1001	2000	31	1001
Bescoby 2006	31	Deans 1983	1002	1983	31	1002
Bescoby 2006	31	Dilke 1992	1003	1992	31	1003
Bescoby 2006	31	Diniz da Costa & Starkey 2001	1004	2001	31	1004
Bescoby 2006	31	Duda & Hart 1973	1005	1973	31	1005
Bescoby 2006	31	Durrani & Bisset 1983	1006	1983	31	1006
Bescoby 2006	31	Giardina & Dougherty 1988	1007	1988	31	1007
Bescoby 2006	31	Hansen & Hodges 2007	1008	2007	31	1008
Bescoby 2006	31	Hodges et al. 2004	1009	2004	31	1009
Bescoby 2006	31	Hounslow & Chroston 2002	1010	2002	31	1010
Bescoby 2006	31	Koike et al. 2005	1011	2005	31	1011
Bescoby 2006	31	Lim 1990	1012	1990	31	1012
Bescoby 2006	31	Magli et al. 1999	1013	1999	31	1013
Bescoby 2006	31	Mugglestone & Renshaw 1998	1014	1998	31	1014
Bescoby 2006	31	Novak & Soulakellis 2000	1015	2000	31	1015
Bescoby 2006	31	Peterson 1992	1016	1992	31	1016

Bescoby 2006	31	Rizakis 1995	1017	1995	31	1017
Bescoby 2006	31	Romano 2003	1018	2003	31	1018
Bescoby 2006	31	Romano & Schoenbrun 1995	1019	1995	31	1019
Bescoby 2006	31	Scollar et al. 1990	694	1990	31	694
Bescoby 2006	31	Vincent 1991	1021	1991	31	1021
Bescoby 2006	31	Waldemark et al. 2000	1022	2000	31	1022
Bescoby 2006	31	Weinstein 1995	1023	1995	31	1023
Dorazio et al. 2012	32	Mena 2003	1024	2003	32	1024
Dorazio et al. 2012	32	Baltsavias 2004	743	2004	32	743
Dorazio et al. 2012	32	Siart et al. 2008	1026	2008	32	1026
Dorazio et al. 2012	32	Kaimaris et al. 2011	1027	2011	32	1027
Dorazio et al. 2012	32	De laet et al. 2007	12	2007	32	12
Dorazio et al. 2012	32	Kucukkaya 2004	1029	2004	32	1029
Dorazio et al. 2012	32	Giardina 2010	1030	2010	32	1030
Dorazio et al. 2012	32	Johnson 2006	1031	2006	32	1031
Dorazio et al. 2012	32	Parcak 2009	392	2009	32	392
Dorazio et al. 2012	32	Ciminale et al. 2009	1033	2009	32	1033
Dorazio et al. 2012	32	Hejcman & Smrz 2010	1034	2010	32	1034
Dorazio et al. 2012	32	Evans & Jones 1977	1035	1977	32	1035
Dorazio et al. 2012	32	Edis et al. 1989	1036	1989	32	1036
Dorazio et al. 2012	32	Mueller et al. 2004	1037	2004	32	1037
Dorazio et al. 2012	32	Fradkin et al. 2001	1038	2001	32	1038
Dorazio et al. 2012	32	Wang et al. 2010	1039	2010	32	1039
Dorazio et al. 2012	32	Gautama et al. 2006	1040	2006	32	1040
Dorazio et al. 2012	32	Chen & Hoi 2008	1041	2008	32	1041
Dorazio et al. 2012	32	Lasaponara & Masini 2011	1042	2011	32	1042
Dorazio et al. 2012	32	Lasaponara & Masini 2007	1043	2007	32	1043
Dorazio et al. 2012	32	Papari & Petkov 2011a	1044	2011	32	1044
Dorazio et al. 2012	32	Tremeau & Bobel 1997	1045	1997	32	1045
Dorazio et al. 2012	32	Shih & Cheng 2005	1046	2005	32	1046
Dorazio et al. 2012	32	Alexakis et al. 2009	1047	2009	32	1047
Dorazio et al. 2012	32	Bucha & Ablameyko 2007	1048	2007	32	1048
Dorazio et al. 2012	32	Kass et al. 1988	1049	1988	32	1049
Dorazio et al. 2012	32	Caselles et al. 1997	1050	1997	32	1050
Dorazio et al. 2012	32	Melonakos et al. 2008	1051	2008	32	1051
Dorazio et al. 2012	32	Zhu et al. 2007	1052	2007	32	1052
Dorazio et al. 2012	32	Zhu et al. 2010	1053	2010	32	1053
Dorazio et al. 2012	32	Lankton & Tannenbaum 2008	1054	2008	32	1054
Dorazio et al. 2012	32	Darolti et al. 2008	1055	2008	32	1055
Dorazio et al. 2012	32	Jing et al. 2011	1056	2011	32	1056
Dorazio et al. 2012	32	Xie 2010	1057	2010	32	1057
Dorazio et al. 2012	32	Krinidis & Chatzis 2009	1058	2009	32	1058
Dorazio et al. 2012	32	Ahmadi et al. 2010a	1059	2010	32	1059

Dorazio et al. 2012	32	Han et al. 2003	1060	2003	32	1060
Dorazio et al. 2012	32	Fang & Chan 2007	1061	2007	32	1061
Dorazio et al. 2012	32	Ma et al. 2010a	1062	2010	32	1062
Dorazio et al. 2012	32	Ma et al. 2011	1063	2011	32	1063
Dorazio et al. 2012	32	Ma et al. 2010b	1064	2010	32	1064
Dorazio et al. 2012	32	Chan & Vese 2001	1065	2001	32	1065
Dorazio et al. 2012	32	Osher & Sethian 1988	1066	1988	32	1066
Dorazio et al. 2012	32	Flusser et al. 2009	1067	2009	32	1067
Dorazio et al. 2012	32	Bradford 1950	1068	1950	32	1068
Dorazio et al. 2012	32	Sandau et al. 2000	1069	2000	32	1069
Dorazio et al. 2012	32	Gonzales et al. 2009	1070	2009	32	1070
Dorazio et al. 2012	32	Rochery et al. 2006	1071	2006	32	1071
Dorazio et al. 2012	32	Stoica et al. 2004	1072	2004	32	1072
Dorazio et al. 2012	32	Yu et al. 2007	1073	2007	32	1073
Dorazio et al. 2012	32	Bas & Erdogmus 2011	1074	2011	32	1074
Dorazio et al. 2012	32	Wang et al. 2011	1075	2011	32	1075
Dorazio et al. 2012	32	Donohue & Ascoli 2011	1076	2011	32	1076
Figorito & Tarantino 2014	33	Agapiou et al. 2012	1077	2012	33	1077
Figorito & Tarantino 2014	33	Ahmadi et al. 2010a	1059	2010	33	1059
Figorito & Tarantino 2014	33	Alexakis et al. 2009	1047	2009	33	1047
Figorito & Tarantino 2014	33	Aqdus et al. 2012	1080	2012	33	1080
Figorito & Tarantino 2014	33	Bucha & Ablameyko 2007	1048	2007	33	1048
Figorito & Tarantino 2014	33	Cao et al. 2008	1082	2008	33	1082
Figorito & Tarantino 2014	33	Chan & Vese 2001	1065	2001	33	1065
Figorito & Tarantino 2014	33	Cramer 2006	1084	2006	33	1084
Figorito & Tarantino 2014	33	De laet et al. 2007	12	2007	33	12
Figorito & Tarantino 2014	33	De Santis et al. 2010	1086	2010	33	1086
Figorito & Tarantino 2014	33	Dorazio et al. 2012	32	2012	33	32
Figorito & Tarantino 2014	33	Eramo et al. 2004	1088	2004	33	1088
Figorito & Tarantino 2014	33	Evans & Jones 1977	1035	1977	33	1035
Figorito & Tarantino 2014	33	Gallo et al. 2009	1090	2009	33	1090
Figorito & Tarantino 2014	33	Gulgen & Gokgoz 2011	1091	2011	33	1091
Figorito & Tarantino 2014	33	Hejcman & Smrz 2010	1034	2010	33	1034
Figorito & Tarantino 2014	33	Lasaponara & Masini 2007	1043	2007	33	1043
Figorito & Tarantino 2014	33	Lasaponara & Masini 2012a	388	2012	33	388
Figorito & Tarantino 2014	33	Lasaponara et al. 2012a	1095	2012	33	1095
Figorito & Tarantino 2014	33	Masini & Lasaponara 2007	1096	2007	33	1096
Figorito & Tarantino 2014	33	Mumford & Shah 2006	1097	2006	33	1097
Figorito & Tarantino 2014	33	Oldfield 2005	1098	2005	33	1098
Figorito & Tarantino 2014	33	Osher & Sethian 1988	1066	1988	33	1066
Figorito & Tarantino 2014	33	Parcak 2009	392	2009	33	392
Figorito & Tarantino 2014	33	Pirotti et al. 2013a	1101	2013	33	1101
Figorito & Tarantino 2014	33	Pirotti et al. 2013b	1102	2013	33	1102

Figorito & Tarantino 2014	33	Sandau et al. 2000	1069	2000	33	1069
Figorito & Tarantino 2014	33	Santoro et al. 2013	1104	2013	33	1104
Figorito & Tarantino 2014	33	Tarantino & Figorito 2011	1105	2011	33	1105
Figorito & Tarantino 2014	33	Vese & Chan 2002	1106	2002	33	1106
Jahjah & Ulivieri 2010	34	Soille & Martino 2002	1107	2002	34	1107
Jahjah & Ulivieri 2010	34	Fukunaga & Koontz 1970	1108	1970	34	1108
Jahjah & Ulivieri 2010	34	Schoelkopf et al. 1999	1109	1999	34	1109
Jahjah & Ulivieri 2010	34	Baudat & Anouar 2000	1110	2000	34	1110
Jahjah & Ulivieri 2010	34	Barber & Ledrew 1991	1111	1991	34	1111
Jahjah & Ulivieri 2010	34	Zhang 1999	1112	1999	34	1112
Jahjah & Ulivieri 2010	34	Laine & Fan 1993	1113	1993	34	1113
Jahjah & Ulivieri 2010	34	Randen & Husoy 1999	1114	1999	34	1114
Jahjah & Ulivieri 2010	34	Lee & Landgrebe 1997	1115	1997	34	1115
Jahjah & Ulivieri 2010	34	Destival 1986	1116	1986	34	1116
Jahjah & Ulivieri 2010	34	Serra & Soille 1994	1117	1994	34	1117
Jahjah & Ulivieri 2010	34	Chou et al. 1994	1118	1994	34	1118
Jahjah & Ulivieri 2010	34	Watson 1987	1119	1987	34	1119
Jahjah & Ulivieri 2010	34	Safa & Flouzat 1989	1120	1989	34	1120
Jahjah & Ulivieri 2010	34	Merring & Parrot 1994	1121	1994	34	1121
Jahjah & Ulivieri 2010	34	Yamada et al. 1993	1122	1993	34	1122
Jahjah & Ulivieri 2010	34	Jahjah et al. 2007	1123	2007	34	1123
Jahjah & Ulivieri 2010	34	Welch & Ahlers 1987	1124	1987	34	1124
Jahjah & Ulivieri 2010	34	Scollar 1990	1125	1990	34	694
Jahjah & Ulivieri 2010	34	Baatz & Schape 1999	1126	1999	34	1126
Jahjah & Ulivieri 2010	34	Duda et al. 2000	192	2000	34	192
Luo et al. 2014a	35	Wilson 2012	1128	2012	35	1128
Luo et al. 2014a	35	Lasaponara & Masini 2012a	388	2012	35	388
Luo et al. 2014a	35	Beazeley 1919	1130	1919	35	1130
Luo et al. 2014a	35	Musson et al. 2006	1131	2006	35	1131
Luo et al. 2014a	35	MeCauley et al. 1982	1132	1982	35	1132
Luo et al. 2014a	35	Moore et al. 2007	1133	2007	35	1133
Luo et al. 2014a	35	Stewarta et al. 2014	1134	2014	35	1134
Luo et al. 2014a	35	Chase et al. 2012	1135	2012	35	1135
Luo et al. 2014a	35	Johnson & Quimet 2014	1136	2014	35	1136
Luo et al. 2014a	35	Aqdus et al. 2012	1080	2012	35	1080
Luo et al. 2014a	35	Atzberger et al. 2014	1138	2014	35	1138
Luo et al. 2014a	35	Cavalli et al. 2007	1139	2007	35	1139
Luo et al. 2014a	35	Challis et al. 2009	1140	2009	35	1140
Luo et al. 2014a	35	De laet et al. 2007	12	2007	35	12
Luo et al. 2014a	35	Lasaponara & Masini 2007	1043	2007	35	1043
Luo et al. 2014a	35	De Laet et al. 2009	378	2009	35	378
Luo et al. 2014a	35	Lasaponara & Masini 2012b	1144	2012	35	1144
Luo et al. 2014a	35	Noviello et al. 2013	1145	2013	35	1145

Luo et al. 2014a	35	Lasaponara & Masini 2014	1146	2014	35	1146
Luo et al. 2014a	35	Luo et al. 2014b	1147	2014	35	1147
Luo et al. 2014a	35	Wonsok et al. 2013	1148	2013	35	1148
Luo et al. 2014a	35	Myers 2010	1149	2010	35	1149
Luo et al. 2014a	35	Sheppard & Cizek 2008	1150	2008	35	1150
Luo et al. 2014a	35	Parks 2009	1151	2009	35	1151
Luo et al. 2014a	35	Kennedy & Bishop 2011	1152	2011	35	1152
Luo et al. 2014a	35	Sadr & Rodier 2012	1153	2012	35	1153
Luo et al. 2014a	35	Kempe & Al-Malabeh 2012	1154	2012	35	1154
Luo et al. 2014a	35	Pringle 2010	1155	2010	35	1155
Luo et al. 2014a	35	Ur 2006	1156	2006	35	1156
Luo et al. 2014a	35	Luo et al. 2012	1157	2012	35	1157
Luo et al. 2014a	35	Morehart 2012	1158	2012	35	1158
Luo et al. 2014a	35	Evans et al. 2007	1159	2007	35	1159
Luo et al. 2014a	35	Doneus et al. 2014	1160	2014	35	1160
Luo et al. 2014a	35	Dorazio et al. 2012	32	2012	35	32
Luo et al. 2014a	35	Lasaponara & Masini 2011	1042	2011	35	1042
Luo et al. 2014a	35	Lasaponara & Masini 2012a	388	2012	35	388
Luo et al. 2014a	35	Agapiou et al. 2013	1164	2013	35	1164
Luo et al. 2014a	35	Tarantino & Figorito 2014	1165	2014	35	1165
Luo et al. 2014a	35	Redfern & Lyons 1998	1166	1998	35	1166
Luo et al. 2014a	35	Jahjah & Ulivieri 2010	34	2010	35	34
Luo et al. 2014a	35	Schuetter et al. 2013	37	2013	35	37
Luo et al. 2014a	35	Trier et al. 2009	248	2009	35	248
Luo et al. 2014a	35	Figorito & Tarantino 2014	33	2014	35	33
Luo et al. 2014a	35	Pasolli et al. 2008	1171	2008	35	1171
Luo et al. 2014a	35	Todd & Mays 2004	1172	2004	35	1172
Luo et al. 2014a	35	Boustani 2009	1173	2009	35	1173
Luo et al. 2014a	35	Karez 2014	1174	2014	35	1174
Luo et al. 2014a	35	Ahmadi et al. 2010b	1175	2010	35	1175
Luo et al. 2014a	35	Moticee et al. 2006	1176	2006	35	1176
Luo et al. 2014a	35	Abudu et al. 2011	1177	2011	35	1177
Luo et al. 2014a	35	Hu et al. 2012	1178	2012	35	1178
Luo et al. 2014a	35	Huang 2003	1179	2003	35	1179
Luo et al. 2014a	35	Li 2005	1180	2005	35	1180
Luo et al. 2014a	35	Hosseini et al. 2010	1181	2010	35	1181
Luo et al. 2014a	35	Haakon & Shen 2006	1182	2006	35	1182
Luo et al. 2014a	35	Haralick et al. 1987	1183	1987	35	1183
Luo et al. 2014a	35	Gonzales & Woods 2002	1184	2002	35	1184
Luo et al. 2014a	35	Maini & Aggarwai 2009	1185	2009	35	1185
Luo et al. 2014a	35	Rahnama & Gloaguen 2014	1186	2014	35	1186
Luo et al. 2014a	35	Canny 1986	594	1986	35	594
Luo et al. 2014a	35	Hough 1962	156	1962	35	156

Luo et al. 2014a	35	Yuen et al. 1989	1189	1989	35	1189
Luo et al. 2014a	35	Rizon et al. 2005	1190	2005	35	1190
Luo et al. 2014a	35	Raymond et al. 1992	1191	1992	35	1191
Luo et al. 2014a	35	Duda & Hart 1972	1192	1972	35	1192
Luo et al. 2014a	35	Shufelt 1999	1193	1999	35	1193
Schneider et al. 2015	36	Bandeira et al. 2012	1194	2012	36	1194
Schneider et al. 2015	36	Bennett et al. 2012	926	2012	36	926
Schneider et al. 2015	36	Bollandsaas et al. 2012	1196	2012	36	1196
Schneider et al. 2015	36	Bond 2007	1197	2007	36	1197
Schneider et al. 2015	36	De Laet et al. 2007	12	2007	36	12
Schneider et al. 2015	36	Deforce et al. 2013	1199	2013	36	1199
Schneider et al. 2015	36	Devereux et al. 2008	1200	2008	36	1200
Schneider et al. 2015	36	Eisank et al. 2014	1201	2014	36	1201
Schneider et al. 2015	36	Groenewoudt 2005	1202	2005	36	1202
Schneider et al. 2015	36	Hesse 2010	1203	2010	36	1203
Schneider et al. 2015	36	Jasiewitcz & Stepinski 2013	1204	2013	36	1204
Schneider et al. 2015	36	Jenness et al. 2013	1205	2013	36	1205
Schneider et al. 2015	36	Kennelly 2008	1206	2008	36	1206
Schneider et al. 2015	36	Lipsdorf 2001	1207	2001	36	1207
Schneider et al. 2015	36	Ludemann 2003	1208	2003	36	1208
Schneider et al. 2015	36	Menze et al. 2006	690	2006	36	690
Schneider et al. 2015	36	Nelle 2003	1210	2003	36	1210
Schneider et al. 2015	36	Nicolay et al. 2014	1211	2014	36	1211
Schneider et al. 2015	36	Nystroem 2014	1212	2014	36	1212
Schneider et al. 2015	36	Pirotti 2010	1213	2010	36	1213
Schneider et al. 2015	36	Pollock 1998	1214	1998	36	1214
Schneider et al. 2015	36	Raab et al. 2014	1215	2014	36	1215
Schneider et al. 2015	36	Risboel et al. 2013	945	2013	36	945
Schneider et al. 2015	36	Roesler 2008	1217	2008	36	1217
Schneider et al. 2015	36	Roesler et al. 2012	1218	2012	36	1218
Schneider et al. 2015	36	Salamuniccar et al. 2014	1219	2014	36	1219
Schneider et al. 2015	36	Sawabe et al. 2006	1220	2006	36	1220
Schneider et al. 2015	36	Schindling & Gibbes 2014	1221	2014	36	1221
Schneider et al. 2015	36	Shruthi et al. 2011	1222	2011	36	1222
Schneider et al. 2015	36	Sofia et al. 2014	1223	2014	36	1223
Schneider et al. 2015	36	Stular et al. 2012	1224	2012	36	1224
Schneider et al. 2015	36	Tarolli et al. 2012	1225	2012	36	1225
Schneider et al. 2015	36	Trier & Piloe 2012	249	2012	36	249
Schneider et al. 2015	36	Trier et al. 2009	248	2009	36	248
Schneider et al. 2015	36	Van den Eeckhaut et al. 2012	1228	2012	36	1228
Schneider et al. 2015	36	Verhagen & Dragut 2012	949	2012	36	949
Schuetter et al. 2013	37	Al-Shahri 2007	1230	2007	37	1230
Schuetter et al. 2013	37	Bin Aqil & McCorriston 2009	1231	2009	37	1231

Schuetter et al. 2013	37	Braemer et al. 2001	1232	2001	37	1232
Schuetter et al. 2013	37	Canny 1986	594	1986	37	594
Schuetter et al. 2013	37	Cashdan 1983	1234	1983	37	1234
Schuetter et al. 2013	37	Cleziou 2001	1235	2001	37	1235
Schuetter et al. 2013	37	Cleziou 2007	1236	2007	37	1236
Schuetter et al. 2013	37	Dalenius 1951	1237	1951	37	1237
Schuetter et al. 2013	37	De Cardi et al. 1977	1238	1977	37	1238
Schuetter et al. 2013	37	De Laet et al. 2007	12	2007	37	12
Schuetter et al. 2013	37	Duda & Hart 1972	1192	1972	37	1192
Schuetter et al. 2013	37	Elwaseif & Slater 2010	1241	2010	37	1241
Schuetter et al. 2013	37	Engelman & Hartigan 1969	1242	1969	37	1242
Schuetter et al. 2013	37	Giger et al. 1988	1243	1988	37	1243
Schuetter et al. 2013	37	Haraliok 1974	1244	1974	37	1244
Schuetter et al. 2013	37	Harrower 2008	1245	2008	37	1245
Schuetter et al. 2013	37	Harrower et al. 2002	1246	2002	37	1246
Schuetter et al. 2013	37	Hough 1962	156	1962	37	156
Schuetter et al. 2013	37	Jensen 1996	369	1996	37	369
Schuetter et al. 2013	37	Kelly 1995	1249	1995	37	1249
Schuetter et al. 2013	37	Lezine et al. 2010	1250	2010	37	1250
Schuetter et al. 2013	37	Lloyd 1982	1251	1982	37	1251
Schuetter et al. 2013	37	McCorriston et al. 2012	1252	2012	37	1252
Schuetter et al. 2013	37	McCorriston et al. 2011	1253	2011	37	1253
Schuetter et al. 2013	37	Menze & Ur 2012	1254	2012	37	1254
Schuetter et al. 2013	37	Okabe et al. 1992	1255	1992	37	1255
Schuetter et al. 2013	37	Proffitt 1982	1256	1982	37	1256
Schuetter et al. 2013	37	Roussillon et al. 2010	1257	2010	37	1257
Schuetter et al. 2013	37	Steimer-Herbert et al. 2006	1258	2006	37	1258
Schuetter et al. 2013	37	Steinhaus 1956	1259	1956	37	1259
Schuetter et al. 2013	37	Stojmenovic & Nayak 2007	1260	2007	37	1260
Schuetter et al. 2013	37	Stojmenovic & Nayak 2006	1261	2006	37	1261
Schuetter et al. 2013	37	Tansey et al. 2009	1262	2009	37	1262
Schuetter et al. 2013	37	Tosi 1986	1263	1986	37	1263
Schuetter et al. 2013	37	Tou & Gonzales 1974	1264	1974	37	1264
Schuetter et al. 2013	37	Tucker 1979	1265	1979	37	1265
Schuetter et al. 2013	37	Zunic & Hirota 2008	1266	2008	37	1266
Vletter 2014	38	Mallet & Bretar 2009	176	2009	38	1267
Vletter 2014	38	Doneus & Briese 2006b	1268	2006	38	1268
Vletter 2014	38	Humme et al. 2006a	1269	2006	38	1269
Vletter 2014	38	Briese 2004a	115	2004	38	115
Vletter 2014	38	Doneus & Briese 2011	1271	2011	38	1271
Vletter 2014	38	Doneus & Briese 2006a	119	2006	38	119
Vletter 2014	38	Djuricic 2012	1273	2012	38	1273
Vletter 2014	38	Briese et al. 2009	2	2009	38	2

Vletter 2014	38	Yokoyama et al. 2002	1275	2002	38	1275
Vletter 2014	38	Doneus 2013	1276	2013	38	1276
Vletter 2014	38	Pregesbauer 2013	1277	2013	38	1277
Lemmens et al. 1993	39	Allen 1984	1278	1984	39	1278
Lemmens et al. 1993	39	Bosma et al. 1989	1279	1989	39	1279
Lemmens et al. 1993	39	Dassie 1978	1280	1978	39	1280
Lemmens et al. 1993	39	Haigh 1983	1281	1983	39	1281
Lemmens et al. 1993	39	Haralick 1984	1282	1984	39	1282
Lemmens et al. 1993	39	Lemmens 1990	1283	1990	39	1283
Lemmens et al. 1993	39	Lemmens 1991	1284	1991	39	1284
Lemmens et al. 1993	39	Limp 1987	1285	1987	39	1285
Lemmens et al. 1993	39	Pratt 1978	1286	1978	39	1286
Lemmens et al. 1993	39	Prewitt 1970	1287	1970	39	1287
Lemmens et al. 1993	39	Roberts 1965	1288	1965	39	1288
Lemmens et al. 1993	39	Scollar 1975	1289	1975	39	1289
Lemmens et al. 1993	39	Scollar 1979	1290	1979	39	1290
Lemmens et al. 1993	39	Scollar et al. 1984	1291	1984	39	1291
Lemmens et al. 1993	39	Wilson 1982	1292	1982	39	1292
Sevara et al. 2016	40	Ackermann 1999	1293	1999	40	1293
Sevara et al. 2016	40	Alt 1990	1294	1990	40	1294
Sevara et al. 2016	40	Arbman 1940	1295	1940	40	1295
Sevara et al. 2016	40	Baatz et al. 2008	742	2008	40	742
Sevara et al. 2016	40	Belgiu & Lampoltshammer 2013	1297	2013	40	1297
Sevara et al. 2016	40	Belgiu et al. 2014a	18	2014	40	18
Sevara et al. 2016	40	Benediksson et al. 1990	1299	1990	40	1299
Sevara et al. 2016	40	Bennett et al. 2014	29	2014	40	29
Sevara et al. 2016	40	Bennett et al. 2012	926	2012	40	926
Sevara et al. 2016	40	Benz et al. 2004	27	2004	40	27
Sevara et al. 2016	40	Bewley et al. 2005	1303	2005	40	1303
Sevara et al. 2016	40	Blaschke 2010	28	2010	40	28
Sevara et al. 2016	40	Blaschke et al. 2014	1305	2014	40	1305
Sevara et al. 2016	40	Blaschke et al. 2000	754	2000	40	754
Sevara et al. 2016	40	De Boer 2005	1	2005	40	1
Sevara et al. 2016	40	Bofinger & Hesse 2011	1308	2011	40	1308
Sevara et al. 2016	40	Briese et al. 2002	653	2002	40	653
Sevara et al. 2016	40	Casana 2014	1310	2014	40	1310
Sevara et al. 2016	40	Challis et al. 2008	1311	2008	40	1311
Sevara et al. 2016	40	Cheung 2005	1312	2005	40	1312
Sevara et al. 2016	40	Cowley 2012	376	2012	40	376
Sevara et al. 2016	40	De Laet et al. 2007	12	2007	40	12
Sevara et al. 2016	40	De Laet et al. 2007a	1315	2007	40	1315
Sevara et al. 2016	40	Devereux et al. 2008	1200	2008	40	1200
Sevara et al. 2016	40	Dey et al. 2010	1317	2010	40	1317

Sevara et al. 2016	40	Doneus 2013	1276	2013	40	1276
Sevara et al. 2016	40	Doneus & Briese 2006	1268	2006	40	1268
Sevara et al. 2016	40	Doneus & Briese 2011	1271	2011	40	1271
Sevara et al. 2016	40	Doneus & Kuehtreiber 2013	1321	2013	40	1321
Sevara et al. 2016	40	Doneus et al. 2008	169	2008	40	169
Sevara et al. 2016	40	Doneus et al. 2001	1323	2001	40	1323
Sevara et al. 2016	40	Dragut & Blaschke 2006	1324	2006	40	1324
Sevara et al. 2016	40	Dragut et al. 2014	1325	2014	40	1325
Sevara et al. 2016	40	Figorito & Tarantino 2014	33	2014	40	33
Sevara et al. 2016	40	Fischer 1997	1327	1997	40	1327
Sevara et al. 2016	40	Harrower et al. 2013	1328	2013	40	1328
Sevara et al. 2016	40	Hay & Castilla 2008	814	2008	40	814
Sevara et al. 2016	40	Hengl & Reuter 2009	1330	2009	40	1330
Sevara et al. 2016	40	Hermodsson 2004	1331	2004	40	1331
Sevara et al. 2016	40	Hesse 2010	1203	2010	40	1203
Sevara et al. 2016	40	Hesse 2014	1333	2014	40	1333
Sevara et al. 2016	40	Hughes 1968	1334	1968	40	1334
Sevara et al. 2016	40	Humme et al. 2006b	1335	2006	40	1335
Sevara et al. 2016	40	Jahjah & Ulivieri 2010	34	2010	40	34
Sevara et al. 2016	40	Kamagata et al. 2005	1337	2005	40	1337
Sevara et al. 2016	40	Kenzler & Lambers 2015	1338	2015	40	1338
Sevara et al. 2016	40	Kettig & Landgrebe 1976	826	1976	40	826
Sevara et al. 2016	40	Kokalj et al. 2011	1340	2011	40	1340
Sevara et al. 2016	40	Kraus & Otepka 2005	1341	2005	40	1341
Sevara et al. 2016	40	Lambers & Zingman 2013	13	2013	40	13
Sevara et al. 2016	40	Lasaponara & Masini 2006	1343	2006	40	1343
Sevara et al. 2016	40	Lasaponara & Masini 2009	1344	2009	40	1344
Sevara et al. 2016	40	Lasaponara et al. 2011b	1345	2011	40	1345
Sevara et al. 2016	40	Lillesand & Kiefer 1994	279	1994	40	279
Sevara et al. 2016	40	Liu & Xia 2010	1347	2010	40	1347
Sevara et al. 2016	40	Loecker et al. 2009	1348	2009	40	1348
Sevara et al. 2016	40	Mahalanobis 1936	1349	1936	40	1349
Sevara et al. 2016	40	Mandlburger et al. 2009b	179	2009	40	179
Sevara et al. 2016	40	Nerman 1918	1351	1918	40	1351
Sevara et al. 2016	40	Neubauer 2012	1352	2012	40	1352
Sevara et al. 2016	40	Neugebauer 1995	1353	1995	40	1353
Sevara et al. 2016	40	Opitz & Cowley 2013	1354	2013	40	1354
Sevara et al. 2016	40	Platt & Rapoza 2008	888	2008	40	888
Sevara et al. 2016	40	Pregesbauer 2013	1277	2013	40	1277
Sevara et al. 2016	40	Schiewe 2002	339	2002	40	339
Sevara et al. 2016	40	Schneider et al. 2015	36	2015	40	36
Sevara et al. 2016	40	Sevara 2013	1359	2013	40	1359
Sevara et al. 2016	40	Sevara & Pregesbauer 2014	1360	2014	40	1360

Sevara et al. 2016	40	Sittler 2004	1361	2004	40	1361
Sevara et al. 2016	40	Smeulders et al. 2000	513	2000	40	513
Sevara et al. 2016	40	Townshend 1981	1363	1981	40	1363
Sevara et al. 2016	40	Townshend et al. 2000	1364	2000	40	1364
Sevara et al. 2016	40	Trier & Piloe 2012	249	2012	40	249
Sevara et al. 2016	40	Trier & Zortea 2015	1366	2015	40	1366
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Sevara et al. 2016	40	Trinks et al. 2014	1368	2014	40	1368
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Sevara et al. 2016	40	Tso & Maher 2009	1370	2009	40	1370
Sevara et al. 2016	40	Verhagen & Dragut 2012	949	2012	40	949
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Sevara et al. 2016	40	Yokoyama et al. 2002	1275	2002	40	1275
Sevara et al. 2016	40	Zaksek et al. 2011	1374	2011	40	1374
Zingman et al. 2016	41	Kothieringer et al. 2015	1375	2015	41	1375
Zingman et al. 2016	41	Lambers & Zingman 2013	13	2013	41	13
Zingman et al. 2016	41	Trier et al. 2009	248	2009	41	248
Zingman et al. 2016	41	Mayer 1999	1378	1999	41	1378
Zingman et al. 2016	41	Lin & Nevatia 1998	1379	1998	41	1379
Zingman et al. 2016	41	Kim & Muller 1999	1380	1999	41	1380
Zingman et al. 2016	41	Croitoru & Doytsher 2004	1381	2004	41	1381
Zingman et al. 2016	41	Jung & Schramm 2004	1382	2004	41	1382
Zingman et al. 2016	41	Krishnamachari & Chellappa 1996	1383	1996	41	1383
Zingman et al. 2016	41	Benedek et al. 2012	1384	2012	41	1384
Zingman et al. 2016	41	Sirmacek & Unsalan 2011	1385	2011	41	1385
Zingman et al. 2016	41	Sirmacek & Unsalan 2009	1386	2009	41	1386
Zingman et al. 2016	41	Manno-Kovacs & Sziranyi 2013	1387	2013	41	1387
Zingman et al. 2016	41	Ortner et al. 2008	1388	2008	41	1388
Zingman et al. 2016	41	Liu et al. 2007b	1389	2007	41	1389
Zingman et al. 2016	41	Keller et al. 2008	1390	2008	41	1390
Zingman et al. 2016	41	Loy & Barnes 2004	1391	2004	41	1391
Zingman et al. 2016	41	Zhu et al. 2003	1392	2003	41	1392
Zingman et al. 2016	41	Yu & Bajaj 2004	1393	2004	41	1393
Zingman et al. 2016	41	Zingman et al. 2013a	1394	2013	41	1394
Zingman et al. 2016	41	Moon et al. 2002	21	2002	41	21
Zingman et al. 2016	41	Descombes & Zerubia 2002	1396	2002	41	1396
Zingman et al. 2016	41	Verdie & Lafarge 2014	1397	2014	41	1397
Zingman et al. 2016	41	Krizhevsky et al. 2012	1398	2012	41	1398
Zingman et al. 2016	41	Simonyan & Zisserman 2015	1399	2015	41	1399
Zingman et al. 2016	41	Chatfield et al. 2014	1400	2014	41	1400
Zingman et al. 2016	41	Sermanet et al. 2014	1401	2014	41	1401
Zingman et al. 2016	41	Szegedy et al. 2015	1402	2015	41	1402
Zingman et al. 2016	41	Dalal & Triggs 2005	1403	2005	41	1403

Zingman et al. 2016	41	Zingman et al. 2014	1404	2014	41	1404
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Zingman et al. 2016	41	Lindeberg 1998	1406	1998	41	1406
Zingman et al. 2016	41	Grigorescu et al. 2004	1407	2004	41	1407
Zingman et al. 2016	41	Papari & Petkov 2011b	1408	2011	41	1408
Zingman et al. 2016	41	Grompone von Gioi et al. 2010	1409	2010	41	1409
Zingman et al. 2016	41	Siddiqi et al. 2002	1410	2002	41	1410
Zingman et al. 2016	41	Pizer et al. 2003	1411	2003	41	1411
Zingman et al. 2016	41	Dimitrov et al. 2003	1412	2003	41	1412
Zingman et al. 2016	41	Engel & Curio 2008	1413	2008	41	1413
Zingman et al. 2016	41	Xu & Prince 1998	1414	1998	41	1414
Zingman et al. 2016	41	Duda & Hart 1972	1192	1972	41	1192
Zingman et al. 2016	41	Lam et al. 1992	1416	1992	41	1416
Zingman et al. 2016	41	Duda & Hart 1973	1417	1973	41	1417
Zingman et al. 2016	41	Bron & Kerbosch 1973	1418	1973	41	1418
Zingman et al. 2016	41	Fukunaga 1990	1419	1990	41	1419
Zingman et al. 2016	41	Devlin et al. 1981	1420	1981	41	1420
Zingman et al. 2016	41	Hariharan et al. 2012	1421	2012	41	1421
Zingman et al. 2016	41	Lambers & Reitmaier 2013	387	2013	41	387
Zingman et al. 2016	41	Zingman et al. 2012	402	2012	41	402
Zingman et al. 2016	41	Otsu 1979	1424	1979	41	1424
Zingman et al. 2016	41	Haykin 2009	1425	2009	41	1425
Zingman et al. 2016	41	LeCun et al. 2015	1426	2015	41	1426
Zingman et al. 2016	41	Oquab et al. 2014	1427	2014	41	1427
Zingman et al. 2016	41	Donahue et al. 2014	1428	2014	41	1428
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Zingman et al. 2016	41	Girshik et al. 2015	1430	2015	41	1430
Zingman et al. 2016	41	Penatti et al. 2015	1431	2015	41	1431
Zingman et al. 2016	41	Russakovsky et al. 2015	1432	2015	41	1432
Zingman et al. 2016	41	Jia et al. 2014	1433	2014	41	1433
Zingman et al. 2016	41	Vedaldi & Lenc 2015	1434	2015	41	1434
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Zingman et al. 2016	41	Krzanowski & Hand 2009	1438	2009	41	1438
Zingman et al. 2016	41	Hanley & McNeil 1982	1439	1982	41	1439
Zingman et al. 2016	41	Pepik et al. 2015	1440	2015	41	1440
Stott et al. 2015	42	Evans 2007	1441	2007	42	1441
Stott et al. 2015	42	Hejcman & Smrz 2010	1034	2010	42	1034
Stott et al. 2015	42	Bennett et al. 2013	1443	2013	42	1443
Stott et al. 2015	42	Beck 2011	1444	2011	42	1444
Stott et al. 2015	42	Jones & Evans 1975	1445	1975	42	1445
Stott et al. 2015	42	Brophy & Cowley 2005	927	2005	42	927

Stott et al. 2015	42	Hejcman et al. 2011	1447	2011	42	1447
Stott et al. 2015	42	Bennett et al. 2012	1448	2012	42	1448
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Stott et al. 2015	42	Mills 2005	1452	2005	42	1452
Stott et al. 2015	42	Cowley & Dickson 2007	1453	2007	42	1453
Stott et al. 2015	42	Rowlands & Sarris 2007	1454	2007	42	1454
Stott et al. 2015	42	Verhoeven 2012	950	2012	42	950
Stott et al. 2015	42	Bernardini et al. 2013	1456	2013	42	1456
Stott et al. 2015	42	Masini & Lasaponara 2013	1457	2013	42	1457
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Stott et al. 2015	42	Chase et al. 2011	1459	2011	42	1459
Stott et al. 2015	42	Evans et al. 2013	1460	2013	42	1460
Stott et al. 2015	42	Johnson & Quimet 2014	1136	2014	42	1136
Stott et al. 2015	42	Cui et al. 2010	1462	2010	42	1462
Stott et al. 2015	42	Challis et al. 2011	1463	2011	42	1463
Stott et al. 2015	42	Challis et al. 2011	1464	2011	42	1464
Stott et al. 2015	42	Briese et al. 2013	1465	2013	42	1465
Stott et al. 2015	42	Briese et al. 2014	1466	2014	42	1466
Stott et al. 2015	42	Hoefle et al. 2012	544	2012	42	544
Stott et al. 2015	42	Doneus & Briese 2006	1468	2006	42	1468
Stott et al. 2015	42	Doneus et al. 2008	169	2008	42	169
Stott et al. 2015	42	Lasaponara et al. 2011b	1345	2011	42	1345
Stott et al. 2015	42	Mallet & Bretar 2009	176	2009	42	176
Stott et al. 2015	42	Wagner et al. 2006	188	2006	42	188
Stott et al. 2015	42	Mallet et al. 2008	1473	2008	42	1473
Stott et al. 2015	42	Anderson et al. 2006	1474	2006	42	1474
Stott et al. 2015	42	Heinzel & Koch 2011	1475	2011	42	1475
Stott et al. 2015	42	Buddenbaum et al. 2013	1476	2013	42	1476
Stott et al. 2015	42	Zhang et al. 2014	1477	2014	42	1477
Stott et al. 2015	42	Lin & Mills 2010	175	2010	42	175
Stott et al. 2015	42	Morsdorf et al. 2006	1479	2006	42	1479
Stott et al. 2015	42	Zhuang & Mountrakis 2014	1480	2014	42	1480
Stott et al. 2015	42	Armitage et al. 2013	1481	2013	42	1481
Stott et al. 2015	42	Blackburn et al. 2014	1482	2014	42	1482
Stott et al. 2015	42	Englhart et al. 2013	1483	2013	42	1483
Stott et al. 2015	42	Hopkinson et al. 2008	1484	2008	42	1484
Stott et al. 2015	42	Pfennigbauer & Ulrich 2011	1485	2011	42	1485
Stott et al. 2015	42	Mesas-Carrascosa et al. 2012	1486	2012	42	1486
Stott et al. 2015	42	Beck 2007	1487	2007	42	1487
Stott et al. 2015	42	Beck et al. 2007	375	2007	42	375
Stott et al. 2015	42	Rosnell & Honkavaara 2012	1489	2012	42	1489

Appendix 4C

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101	BRADLEY, R.; SMALL, C. (1985) - Looking for circular structures in post hole distributions: Quantitative analysis of BRADLEY, R.; SMALL, C. (1985) - Looking for circular structures in post hole distributions: Quantitative analysis of two settlements from bronze age England. Journal ofArchaeological Science, 12, p. 285-297.
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LIDAR based semi-automatic
pattern recognition within
an archaeological landscape

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