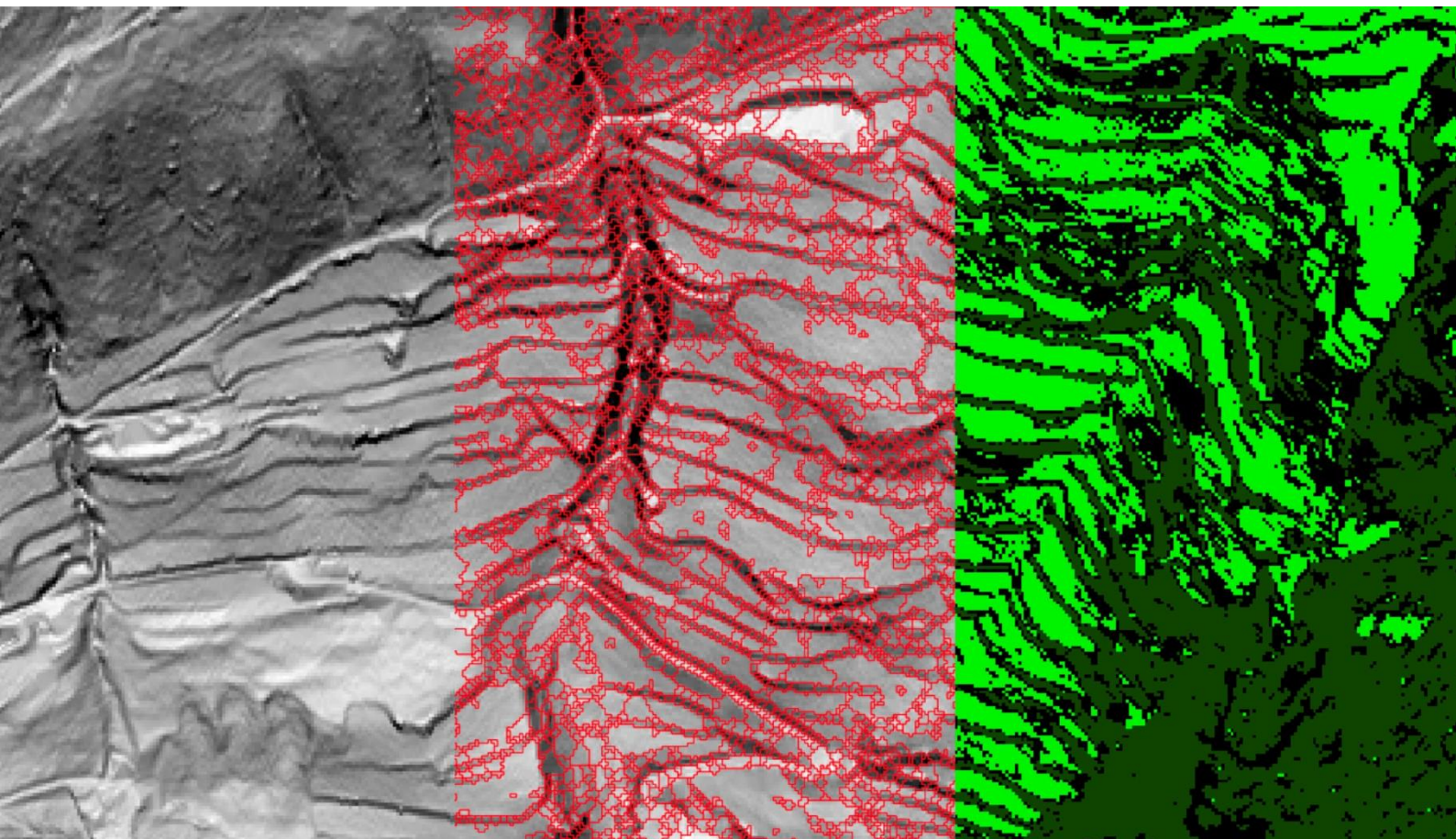


Step by Step

Developing a Geographic Object-Based Image Analysis
Workflow for the Terraced Landscape of the Lower
Engadine, Switzerland



Pierina Roffler

Front cover: Hillshade visualisation of DTM (Bundesamt für Landestopografie, 2019)
using RVT 2.2.1 (Kokalj and Somrak 2019), watershed segmentation and classification.
Design by Pierina Roffler.

Step by Step: Developing a Geographic Object-Based Image Analysis Workflow for the Terraced Landscape of the Lower Engadine, Switzerland

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Table of Contents

Acknowledgements	6
1. Introduction.....	7
1.1. Research context	7
1.1.1. Methodological background.....	7
1.1.2. Archaeological background	9
1.2. Aims and research questions	11
1.3. Data and methodology	12
1.3.1. SwissALTI ^{3D}	12
1.3.2. Other data.....	13
1.3.3. Methodology	13
1.4. Structure	14
2. Semi-automatic image analysis – friend or foe?	15
2.1. Automated solutions for ever growing datasets	15
2.2. Object Detection Methods.....	17
2.3. Insert: The terraced landscape of the Lower Engadine, Switzerland	18
2.3.1. Location, Geology and Morphology	18
2.3.2. Human activity in the landscape through the ages	20
2.3.3. Terrace types	22
2.3.4. Future of the terraces.....	25
2.4. Pixels versus objects	25
2.5. Conclusion	27
3. Introduction to GeOBIA	29
3.1. Terminology, history and evolution of GeOBIA	29
3.2. Methodology	29
3.2.1. Segmentation.....	31
3.2.2. Overview of segmentation algorithms	31
3.2.3. Semantic, hierarchical classification.....	35
3.3. Current Issues.....	37
3.3.1. FOSS	37
3.3.2. Segmentation parameter selection.....	38
3.4. Objectives and Potential.....	39
3.5. Conclusion	40
4. Testing existing software solutions with a GUI.....	41
4.1. Test criteria and process.....	41
4.2. Proprietary software	42

4.2.1.	Trimble eCognition	42
4.2.2.	ERDAS IMAGINE	43
4.3.	FOSS	45
4.3.1.	SAGA GIS	45
4.3.2.	QGIS	47
4.3.2.1.	Semi-automatic classification plugin (SCP)	47
4.3.2.2.	Orfeo Toolbox.....	48
4.3.3.	GRASS GIS	51
4.3.4.	Other software.....	52
4.4.	Discussion and Conclusion	53
5.	Developing a custom GeOBIA workflow	56
5.1.	Testing phase.....	56
5.1.1.	LiDAR visualisations	57
5.1.2.	Objects requiring classification.....	67
5.1.3.	Training data	68
5.1.4.	Smoothing filters and segmentation algorithms.....	69
5.1.5.	Identification of different terrace types.....	73
5.2.	Final workflow	74
5.3.	Semi-automation in the QGIS graphical workflow modeller	76
5.4.	Results.....	77
5.4.1.	Transferability.....	80
5.5.	Discussion and Conclusion	81
6.	The benefits of a semi-automatic image analysis workflow	83
6.1.	Survey setup.....	83
6.2.	Limitations of the survey	85
6.3.	Survey results.....	86
6.3.1.	Group one (TERRA participants)	86
6.3.2.	Group two (no prior knowledge).....	91
6.4.	Comparison of the results generated by the two user groups.....	96
6.5.	A note on bias and time savings.....	98
6.6.	Discussion and Conclusion	98
7.	Conclusion and outlook.....	101
	Abstract.....	105
	Bibliography.....	107
	List of figures	113
	List of tables.....	116

List of appendices	117
Appendix i.....	119
Appendix ii.....	120
Appendix iii.....	122
Appendix iv.....	124
Appendix v.....	126
Appendix vi.....	128

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1. Introduction

Nowadays, highly accurate remotely sensed data can be acquired rapidly and in large amounts due to many technical advances in the field. The ever growing complexity of digital remote sensing data has led to a wide range of computational tools being developed in the fields of geodesy, cartography and earth observation (Lambers 2018, 115). However, the interpretation of this data in archaeology is still largely a manual undertaking that is not in proportion with the quantity and complexity of multi and even hyperspectral images (Lambers 2018, 115). Unfortunately, existing tools for object detection from fields other than archaeology usually fail when targeting the faint, elusive archaeological traces (Lambers 2018, 115). For this reason, semi-automatic or even fully automatic solutions for the interpretation of archaeological remotely sensed data need to be developed and it is important that these solutions are uncomplicated but effective in order to ensure their large-scale adoption.

1.1. Research context

This thesis focuses primarily on the methodological aspects of developing a semi-automatic image analysis workflow and its application to a study area. Because the choice of semi-automatic image analysis technique depended largely on the study area that it is to be applied to, the research context must be split into two parts. First the methodological background as well as the choice of methods will be explained and subsequently, the archaeological background and study area will be introduced.

1.1.1. Methodological background

In the last few years, the number of remotely sensed, highly accurate datasets has increased exponentially (Bennett *et al.* 2014, Opitz and Herrmann 2018, 19). Airborne Laser Scanning (ALS) and the generation of detailed Digital Terrain Models (DTMs) is particularly well suited to detect subtle features in the topography that would go unnoticed in a traditional landscape survey (Sevara *et al.* 2016, 485). Especially in forested areas, laser scanning enables archaeological observations that would be difficult using traditional survey methods and practically impossible using aerial photographs. However, interpreting this remote sensing data is very time consuming and at the present day, it is possible to produce such large quantities of high-resolution data, that it is becoming increasingly

difficult to interpret it all manually (Lambers *et al.* 2019, 794; Sevara *et al.* 2016, 485).

A solution for coping with the large amount of remotely sensed data is the (semi)-automation of image analysis (Magnini and Bettineschi 2009, 10; Meyer *et al.* 2019, 108, Opitz and Herrmann 2018, 30). An added benefit of (semi)-automatic image analysis is the improved rate and consistency of feature detection over large areas (Opitz and Herrmann 2018, 30), as well as better reproducibility and accessibility of the interpretation of said imagery (Magnini and Bettineschi 2019, 10). Semi-automatic image analysis methods can be roughly divided into two groups: pixel-based and object-based approaches. Pixel-based approaches utilise the properties of each pixel in order to detect features (Sevara *et al.* 2016, 487), while object-based approaches segment the entire image into groups of pixels that all express similar properties (Sevara *et al.* 2016, 487; Chen and Han 2016, 16).

In their 2016 study, Sevara *et al.* have applied both pixel-based and object-based image analysis methods to two study areas. The first was a homogeneous landscape containing burial mounds (Sevara *et al.* 2016, 489), the second was a heterogeneous landscape containing various linear archaeological objects belonging to a hillfort (Sevara *et al.* 2016, 489). The researchers came to the conclusion that in both cases, but especially in the case of heterogeneous and linear objects, object-based image analysis is much more precise than pixel-based image analysis (Sevara *et al.* 2016, 496). Because the archaeological objects under study are linear and located in a very heterogeneous landscape, this thesis will focus on Geographic Object-Based Image Analysis (GeOBIA).

There are a number of studies that have applied GeOBIA and many researchers make use of the commercial software Trimble eCognition (see for example: Meyer *et al.* 2019; Sevara *et al.* 2016; Kramer 2015). Trimble eCognition is very costly and some institutions will not have the budget to purchase this software. In addition, the source code is proprietary, which hinders reproducibility and adaptability of the developed methods.

There is still scepticism about GeOBIA and the (semi-) automation of image analysis in general. Critics argue that only a human image interpreter can cope with the diverse and complex shapes, sizes and spectral properties of archaeological objects (Traviglia *et al.* 2016 provide a nice overview of the reservations towards

computer based approaches to image analysis). The human brain has the ability to identify patterns, although this skill can sometimes mislead (Bennet *et al.* 2014, 899) and a manual approach reproduces, rather than overcomes biases (Lambers *et al.* 2019, 794). The interpreter's expectations about archaeological objects can cause the misclassification of an object or cause objects to be overlooked entirely because their appearance does not match the interpreter's expectations (Cowley 2016, 159). A computer algorithm, although not as flexible in the interpretation of images as a human mind, is more unbiased as it solely classifies features that match the specified attributes (Bennet *et al.* 2014, 899). In addition, the algorithm will be consistent across large datasets, is replicable (Bennet *et al.* 2014, 899), and computer-based approaches oblige researchers to define more clearly what they are looking for, thus highlighting possible inconsistencies of approach (Cowley 2016, 159). The strengths and weaknesses of semi-automated image analysis, as well as the current state of the research will be discussed further in chapter 2.

1.1.2. Archaeological background

The terraced landscape of the Lower Engadine, located in the canton of Grisons in Switzerland (figure i), is currently under study in the context of an inter-institutional research project called TERRA (Terraced Landscapes of the Lower Engadine, Switzerland). In a co-operation of the universities of Bamberg, Heidelberg, Leiden and Zurich, as well as the Archaeological Services of the Canton of Grisons, the landscape of the area has been surveyed extensively over the course of 6 years. The research area in the Lower Engadine spans the northern flank of the Inn valley, particularly the hillside around the present-day village of Ramosch.

The following paragraph is based on information that was gathered from the project websites of the Universities of Leiden and Zurich, as well as from the official project site of the Archaeological Services of the Canton of Grisons.¹ It is the aim of the project to analyse the earliest anthropogenic influences on the landscape as well as to study the role of the terraces in prehistoric resource management of the

¹ Leiden: <https://www.universiteitleiden.nl/en/research/research-projects/archaeology/terraced-landscapes-of-the-lower-engadine-switzerland>

Zurich: [http://www.archaeologie.uzh.ch/de/prehist/forschung/Projekte/TERRA-\(Terrassenlandschaft-Ramosch-Untereengadin\).html#publication](http://www.archaeologie.uzh.ch/de/prehist/forschung/Projekte/TERRA-(Terrassenlandschaft-Ramosch-Untereengadin).html#publication)

Archaeological Services of the Canton of Grisons :

<https://www.gr.ch/DE/institutionen/verwaltung/ekud/afk/adg/projekte/Seiten/start.aspx>

[all accessed: 28.01.20]

Alps. To this effect methods such as regional 3D-mapping based on remotely sensed data, geophysical as well as archaeological survey, soil and sediment analysis, stratigraphical excavations and chronometric dating were applied to the study area. The studied archaeological objects are the terraces themselves, but also irrigation ditches, old paths, abandoned alp settlements as well as the hilltop sites Ramosch Motta and Mottata. Ramosch Mottata dates into the Bronze and Iron Age (Frei 1958, 36).

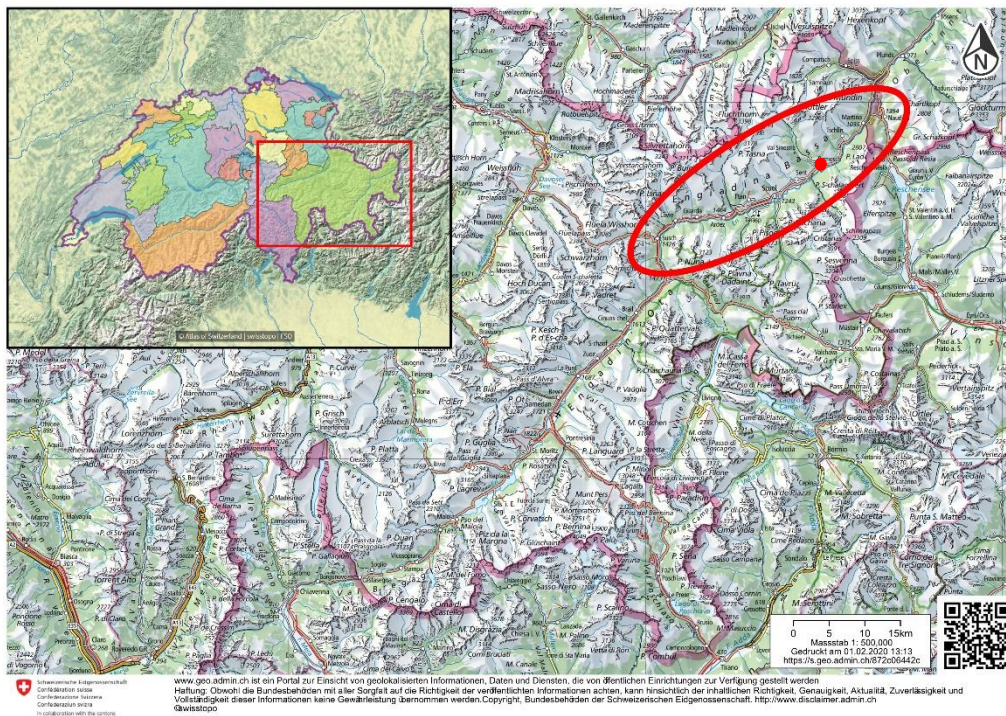


Figure i: The Lower Engadine valley (marked with a red ellipse) is located in the far eastern part of the canton of Grisons (marked with a red rectangle). The present-day village of Ramosch is marked with a red dot. (Bundesamt für Landestopografie, 2019 and <https://www.atlasderschweiz.ch/de> (Institute of Cartography and Geoinformation, ETH Zurich)). Editing: Pierina Roffler.

Figure ii shows the study area of this thesis as well as the present day villages of Ramosch and Vnà, and the prehistoric hilltop settlement of Ramosch Mottata. The study area can be split into an upper and a lower part. In the lower part of the study area, the agricultural terraces are very well preserved while in the upper part, they are more eroded and thus less recognizable in the landscape, making traditional landscape survey and archaeological object mapping a difficult task (Chapter 2.3.3). This is where the use of Airborne Laser Scanning (ALS) comes into play. It is the hope that Digital Terrain Models (DTMs) derived from LiDAR (Light Detection And Ranging) data can significantly aid the recognition and classification of further archaeological objects in the study area. As mentioned in chapter 1.1.1, the manual

interpretation of images such as LiDAR visualisation can be difficult, and a semi-automatic classification workflow could greatly facilitate the image analysis.

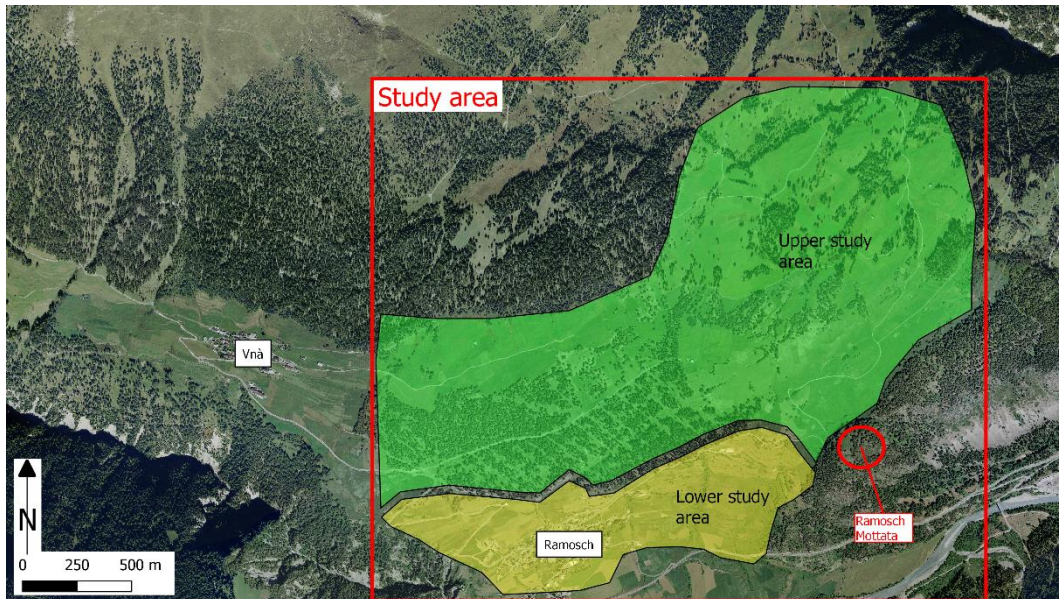


Figure ii: The study area of this thesis, which can be split into an upper and a lower part. (Bundesamt für Landestopografie, 2019). Editing: Pierina Roffler.

1.2. Aims and research questions

Most archaeologists do not have a background in programming and may have more difficulty developing their own algorithms. It is thus important to find common ways for publishing rule-set libraries for semi-automatic and automatic image analysis (Magnini and Bettineschi 2019, 11), but also to have easily accessible, effective and open source software for GeOBIA with a Graphical User Interface (GUI) that does not require the user's knowledge of a programming language. The first aim of this thesis is to provide an overview of the existing free and open-source (FOSS) GeOBIA applications and to assess the user friendliness and effectiveness of each programme. During this process, it is the aim to point out which required functions are missing in readily available software solutions. The research question that corresponds to this aim is the following:

Is there an open source solution for GeOBIA available with a Graphical User Interface (GUI) that is user friendly, does not require additional coding and will prove through systematic testing to be capable of classifying the heterogeneous and linear features within the terraced landscape of the Lower Engadine?

Secondly, it is the aim to create a custom GeOBIA workflow for the heterogeneous landscape of the Lower Engadine. This workflow will use only FOSS applications

as this again promotes accessibility, transparency and reproducibility of the research. This aim can be summarized by the research question:

What are the elements that an effective GeOBIA workflow for heterogeneous and linear archaeological objects needs to contain?

Finally yet importantly, it is the aim to find out whether a semi-automatic image analysis workflow could be beneficial to the user or whether the LiDAR visualisation on its own is still the most intuitive basis for manual classification. The research question that corresponds to this aim is:

Does the developed workflow deliver results that save time and support the human interpreter?

The next section will introduce the data and the methodology that were applied in order to answer these three research questions.

1.3. Data and methodology

1.3.1. SwissALTI^{3D}

For testing available GeOBIA solutions as well as for the development of the custom workflow, a DTM of the study area was used. The following section bases on information obtained from the product information brochure provided by swisstopo, the Swiss national topography agency (Bundesamt für Landestopografie swisstopo, 2018).

The so-called SwissALTI^{3D} is a DTM that is updated yearly and provided to the user as raster dataset or xyz-file of a regular grid with cells of 2 x 2 meters where each cell of the grid contains a height information. The source of the height information and the accuracy of the DTM depends on the area that the DTM covers. This information is summarised in table i.

Table i: Summary of SwissALTI^{3D} data sources and accuracies.		
	Below 2000 m a. s. l.	Above 2000 m a. s. l.
Data source	LiDAR scans	Stereocorrelation ²
Accuracy	±50cm 1σ	±1m – 3m 1σ

² Generation of height data by comparing two aerial photographs with a high overlap and sufficiently differing camera angles

The SwissALTI^{3D} is publicly available for download by creating a free login on the GeoGR website (<https://www.geogr.ch/>). The reason for choosing to work with an already filtered DTM is that oftentimes, the original, unfiltered Digital Surface Models (DSMs) are not available to archaeologists and the workflow developed in this thesis should be fully reproducible.

1.3.2. Other data

Aerial photos and maps of the area will be used in addition to the DTM for orientation purposes. The maps are also free to download with a GeoGR login, while the aerial photos are provided by the Swiss national topography agency swisstopo and are only available upon request and with a personal download id. In order to assess the effectiveness of the GeOBIA workflow, the final results will be compared to manual mapping results. Angelika Abderhalden-Raba mapped the terraces, roads, drainages and many more features in the context of her dissertation in 1996 (Raba 1996), Emily Vella mapped the lower terraces and waterways during the course of her Leiden University master's thesis (Vella 2018), and Philippe Della Casa, a TERRA project member from the University of Zurich, mapped the upper archaeological objects during the fieldwork campaigns between 2015 and 2019.

1.3.3. Methodology

Firstly, different visualisations of the DTM will be generated with the Relief Visualisation Toolbox (RVT) version 2.2.1 (Kokalj and Somrak 2019; Zakšek *et al.* 2011). These visualisations are then imported into different FOSS and proprietary software. In each of the tested software, a GeOBIA workflow will be carried out. This process enables the assessment of the user friendliness, as well as the effectiveness and suitability of each software package and highlights the necessary, but also the missing steps of the GeOBIA workflow. It also enables a comparison between the FOSS and the proprietary software solutions, highlighting the benefits and drawbacks of each programme. After this first phase of practical thesis research, the first research question will be answered.

In order to answer the second research question, the next phase comprises of developing the GeOBIA workflow for the terraced landscape of the Lower Engadine, testing different pre-processing steps and segmentation algorithms in the

progress. Only open source software will be utilised to develop this workflow in order to promote accessibility, transparency and reproducibility of the workflow.

Finally, the effectiveness, as well as the accuracy of the workflow will be assessed by comparing the resulting classification with the manual mapping of the area. Additionally, a survey will be conducted in order to assess whether or not the resulting classification is beneficial to human interpreters, answering the third research question in the process.

1.4. Structure

In the next chapter, the necessity of (semi-)automatic image analysis solutions will be discussed before presenting some of the most common object detection methods. Additionally, the next chapter will provide more in-depth information about the study area that the final workflow will be applied to, explaining the motivation for the choice of methods. The third chapter presents more technical in-depth information about GeOBIA before highlighting some of the current issues in the field. The fourth chapter is dedicated to the efficiency analysis of different open source and proprietary GeOBIA software with a Graphical User Interface (GUI), their effectiveness and user friendliness, while the fifth chapter will contain the GeOBIA workflow design and implication. These two chapters are followed by the presentation and discussion of the user feedbacks as well as the assessment of the benefits that can be gained from such a GeOBIA workflow. After each of these more practical chapters, the results are discussed and finally, the thesis is rounded off with a conclusion as well as an outlook on future research.

2. Semi-automatic image analysis – friend or foe?

This chapter will go into further depth on the subject of approaches to semi-automatic image analysis of remote sensing data. It will present some of the reservations that researchers have towards semi-automatic approaches, but mainly highlight the acute need for new technologies and their benefits. Furthermore, it will present the archaeological study area and explain why Geographic Object-Based Image Analysis (GeOBIA) was chosen in this particular case.

2.1. Automated solutions for ever growing datasets

Remote sensing data are increasingly becoming available at very high resolutions, great frequency of acquisition and low costs, also to archaeologists (Bennet *et al.* 2014, 896). Some of this data comes at such a high spectral, spatial or temporal resolution that some objects of interest are not visible to the naked human eye (Sevara *et al.* 2016, 485). However, despite all the technological advances in image data acquisition, the interpretation of such images is still largely manual (Bennet *et al.* 2014, 867). The manual interpretation of remote sensing data, however, is becoming increasingly difficult (Sevara *et al.* 2016, 485), time consuming and requires a lot of resources (Bennet *et al.* 2014, 867). More importantly, it does not do justice to the depth of content that modern air- and space borne spectral systems have to offer (Bennet *et al.* 2014, 898). Speeding up the analysis of large amounts of data also has the benefit of contributing to the management and protection of the archaeological record (Magnini and Bettineschi 2019, 11). The faster objects are detected, the sooner they can be preserved or at least documented before their destruction.

In order to work with this new generation of remotely sensed images, a reassessment of established workflows is needed, as well as a clearer understanding of the possibilities of using computer-aided methods for object detection (Bennet *et al.* 2014, 896). The automation or semi-automation of image analysis is a possibility for speeding up the process and has the added benefit of granting better reproducibility for image classifications and interpretations (Magnini and Bettineschi 2019, 10). Initially, despite all the aforementioned benefits, computer-aided classification and interpretation of images was rarely used and viewed with suspicion (Bennet *et al.* 2014, 896).

Bennet *et al.* (2014) note that new remote sensing technologies for archaeological prospection have had to rely on data and image processing expertise from other fields, and that this has led to poor communication as well as over enthusiastic claims of success (Bennet *et al.* 2014, 898). This is due to the fact that archaeologists deal with different features than the environmental and geological remote sensing communities, and because archaeologists do not only have to detect features or classes, but also need to interpret them across a landscape (Bennet *et al.* 2014, 898). As a result, some archaeologists feared that the expertise in archaeological interpretation is undervalued in the semi-automatic or automatic image analysis (Bennet *et al.* 2014, 898), and that the archaeological experience and knowledge could be left out of the interpretative process entirely. For example, Palmer and Cowley state that:

“It is argued that interpretation of aerial images is a specialist skill, improved by experience and that methods of auto extraction, often applied to unsuitable images, are a poor substitute for this (Palmer and Cowley 2010, 129).”

However, as Cowley discusses in one of his later papers, the human vision and judgement can sometimes mislead (Cowley 2016, 158). Archaeological interpretations are based on the experience, knowledge and observational ability of the interpreter and this knowledge can bias what an interpreter sees or does not see and how the detected objects are interpreted (Cowley 2016, 158; Bennet *et al.* 2014, 899). A computer algorithm on the other hand, while not being as flexible as a human interpreter, removes a major source of bias in detection as it is not able to filter or rationalise a mass of visual information, but rather searches for set criteria (Bennet *et al.* 2014, 899).

Although the computer algorithm is very good at strictly detecting a set of criteria, it does not provide archaeological interpretations (Bennet *et al.* 2014, 899). The goal should therefore be to find ways to use the computer-aided techniques and combine them with expert knowledge about the archaeological record (Sevara *et al.* 2016, 485). The archaeologist has an important role in the process of image classification and subsequent interpretation, and thus the automation should be seen as an aid rather than a substitute of traditional manual interpretation, or, in the words of Traviglia *et al.*: “[...] no one advocates ‘automatic archaeology’ [...]” (2016, 12). Because the human interpreter has an important role in the semi-automatic

image analysis workflow, the fear of critics that the expert may be replaced entirely by a computer algorithm is unfounded.

2.2. Object Detection Methods

Cheng and Han (2016) define the goal of object detection in remote sensing images as follows:

“[...] to determine if a given aerial or satellite image contains one or more objects belonging to the class of interest and locate the position of each predicted object in the image (Cheng and Han 2016, 11).”

There are several different methods for the (semi-)automatic analysis of images. Cheng and Han (2016) differentiate between object detection by template matching, knowledge-based object detection, object-based image analysis (OBIA) and machine learning-based object detection methods (Cheng and Han 2016, 12). Lambers *et al.* (2019) have applied the taxonomy of Cheng and Han (2016) to examples of archaeological research (Lambers *et al.* 2019, 2). Cheng and Han (2016) go on to state that these categories are not necessarily independent and that sometimes the same method can be placed in different categories (Cheng and Han 2016, 12).

Template matching utilises a hand crafted template for each object class that is to be detected, which is then placed over each possible position in the image in order to find best matches (Cheng and Han 2016, 13). Knowledge-based object detection involves developing specific rulesets for the objects based on specific knowledge about the geometry or the context of these objects (Cheng and Han 2016, 15). The introduction already briefly introduced the concept of GeOBIA, but as a reminder: OBIA-based object-detection (for geospatial objects: GeOBIA) involves segmenting the entire image into homogeneous areas called segments and subsequently classifying the entire image using training data from meaningful segments (Cheng and Han 2016, 15). Finally, machine learning-based object detection utilises a classifier that is taught variations in object appearances and views from a set of training data. This classifier is then fed a set of regions (or object proposals) with feature representations and then outputs their corresponding predicted object labels (Cheng and Han 2016, 16).

Davis 2018 and Davis *et al.* 2019 define different categories; for example, they define template-matching as an OBIA approach (Davis *et al.* 2019a, 27; Davis *et*

al. 2019b, 169) and OBIA as a form of machine-learning (Davis 2018, 1). Nevertheless, in this thesis, the author has decided to adopt the definitions of Cheng and Han 2016.

As the title and the introduction of this thesis already show, GeOBIA was selected as the semi-automatic object detection method of choice. In order to show the motivation for this choice, it is necessary to take a closer look at the particularities of the study area.

2.3. Insert: The terraced landscape of the Lower Engadine, Switzerland

2.3.1. Location, Geology and Morphology

The main study area of the TERRA project is the area around the village of Ramosch which is located in the Lower Engadine Valley. The Lower Engadine is a part of the canton of Grisons in Switzerland. It starts at Punt Ota in between S-Chanf and Zernez and continues in a north-eastern direction along the Inn River until the border to Austria and Italy respectively. Flanking the valley are two mountain chains that reach heights of 3000 – 3400 meters above sea level.

The valley was glaciated until 11000 BC and the present-day morphology clearly shows the maximum extent of the glacier (Raba 1996, 13). Only the highest peaks remained free of the ice masses, the rest of the valley was deformed, a process that is still visible in the landscape morphology today (Raba 1996, 13). The region is mainly composed of metamorphic rocks that are part of the Eastern Alpine Silvretta crystalline (Kothieringer *et al.* 2015, 179). A particularity of this region is the Lower Engadine window, where there are outcrops of sedimentary Penninic rocks which are usually covered by the crystalline (Kothieringer *et al.* 2015, 179). Figure iii shows the Lower Engadine window.

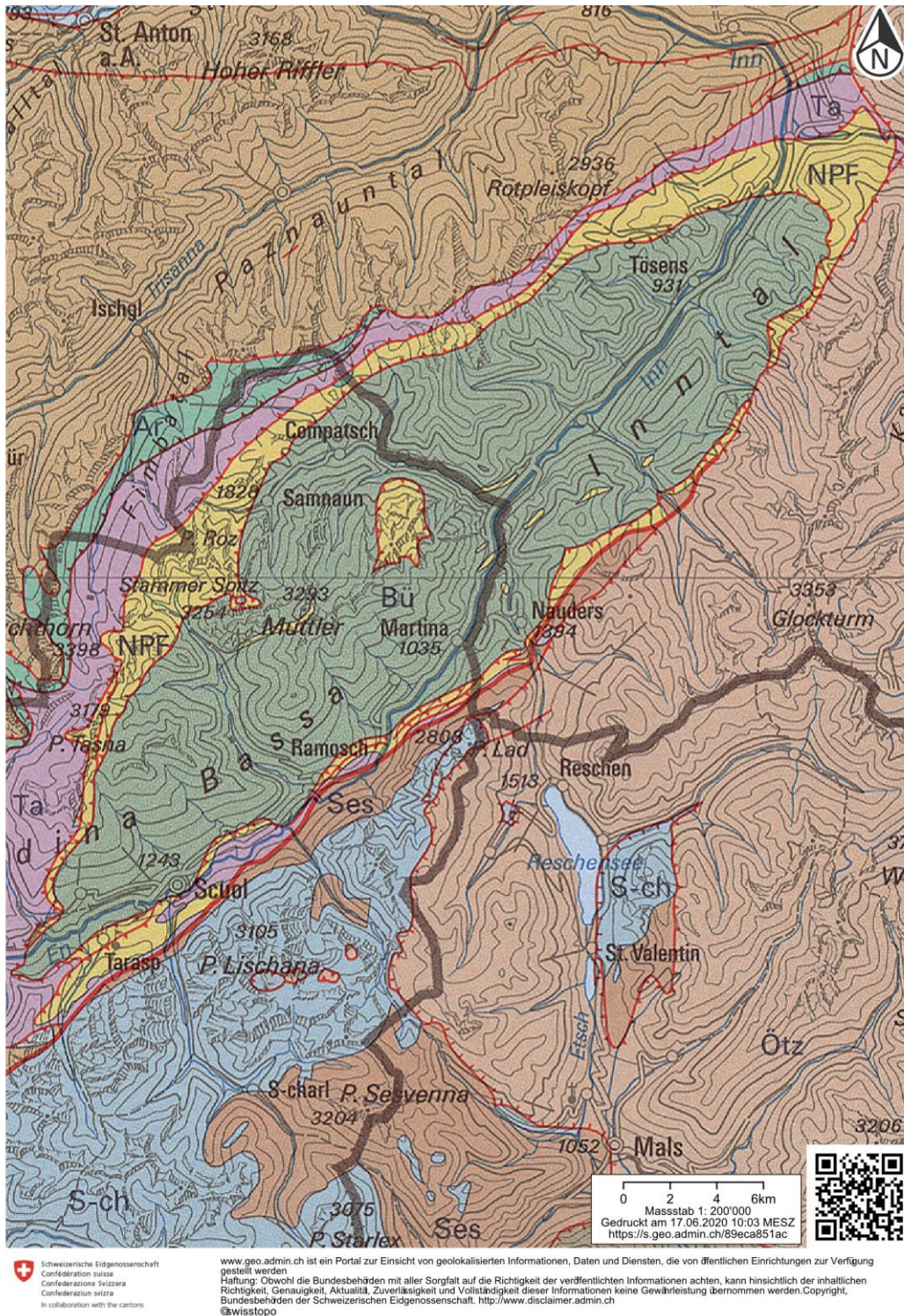


Figure iii: The Lower Engadine Window with the outcrops of sedimentary Penninic rocks (green) and the metamorphic rocks of the Eastern Alpine Silvretta cristaline (brown) (Bundesamt für Landestopografie, 2020).

Looking upstream the Inn river (western direction), the right valley side is comprised of Bündner schist, the left side of the valley is composed of dolomite rock (Raba 1996, 13). The different rock types on each side of the valley also mean that the glacial deformation processes left different marks; the right side is much softer than the rugged, left side of the valley (Raba 1996, 8). The right side was

formed to a broad valley floor with rounded landscape features (Kothieringer *et al.* 2015, 180) and it receives considerably more sunlight than the left side of the valley (Raba 1996, 8). These differences led to different anthropic uses of the valley sides with the left, rugged side being mostly forested and the right, soft side being used for settlements and agriculture (Raba 1996, 8). Figure iv clearly shows that the right side of the valley is softer and contains settlements and agricultural fields, while the left hand side is steep and forested. Because the metamorphic rocks such as Bündner schist are morphologically less resistant, they have been very susceptible to weathering and erosion (Kothieringer *et al.* 2015, 179), a fact that makes the determination of archaeological features a difficult task.



Figure iv: A view upstream the Inn River (western direction) with the village of Ramosch on the right hand side. The left side of the valley is composed of dolomite rock and is much more rugged than the right side which consists of Bündner schist. The right side also receives considerably more sunlight and is used for settlements and agriculture while the left side is largely forested (Jonas Blum).

2.3.2. Human activity in the landscape through the ages

The palynological evidence shows that the earliest agriculture began during the late Neolithic and Early Bronze Age (Zoller *et al.* 1996, 49). Interestingly, the earliest cultivation is proved at high altitudes from the Early Bronze Age onwards while in lower situated regions agriculture began distinctly later (Zoller *et al.* 1996, 49). Zoller *et al.* (1996) note that it seems that the fields in the vicinity of Ramosch-Vnà

were gradually established from the higher located parts to the lower ones (Zoller *et al.* 1996, 49).

Additionally, there is archaeological evidence for the presence of hunters, gatherers and travellers in the study area during the Neolithic period (Kothieringer *et al.* 2015, 190). This evidence is supported by palaeo-environmental evidence that suggests human impact on both vegetation and soils, most likely from forest clearances by fire and livestock grazing (Dietre *et al.* 2020, 364; Dietre *et al.* 2017, 192; Kothieringer *et al.* 2015, 190). Additionally, the first cereal-type pollen was found in the stratigraphy of the Las Gondas bog, where the pollen grains from the Lower Engadine were probably deposited by means of long-distance air transport or by local deposition of livestock faeces (Kothieringer *et al.* 2015, 189).

During the Late Neolithic, both the archaeological and the palaeo-environmental record show that the human impact on the landscape increases (Kothieringer *et al.* 2015, 190). Field terracing has been recorded since at least 2800 BC and thus the economic system of resource exploitation covered different vertical ecozones (Kothieringer *et al.* 2015, 195). From the Bronze Age onwards, both archaeological and palaeo-environmental data shows human impact in high-altitude areas (Kothieringer *et al.* 2015, 194; Dietre *et al.* 2014, 13). This is part of a trend towards a general intensification of occupation and use of the inner alpine zone during this time (Kothieringer *et al.* 2015, 194). This trend also led to more and more permanent settlements in the area, such as the Bronze and Iron Age settlement Ramosch Mottata that is located within the study area of this thesis (Frei 1958, 36).

The subsistence basis for settlements, such as Ramosch Mottata, was an interdependent combination of small scale agriculture and intensive animal husbandry that allowed the best possible utilisation of the available resources (Reitmaier and Kruse 2018, 268). When Reitmaier *et al.* (2018) combined new radiocarbon dates and high-resolution strontium isotope analysis of bovine tooth enamel from the settlement Ramosch-Mottata, they noticed that alpine animal management during the late Bronze Age changed from great variability in mobility patterns to a much more uniform, seasonal mobility (Reitmaier *et al.* 2018, 29). They explain this change in mobility patterns with a change from exploiting animals for their primary products (meat, hide and bone) to the exploitation of their secondary products (milk and wool) (Reitmaier *et al.* 2018, 28). Animals that are

used for their primary product are allowed to graze more freely throughout the pasture grounds as there is no need to enclose them, while animals that are used for their secondary products require pens and seasonal buildings for milk processing and storing of dairy products (Reitmaier et al 2018, 28).

During the Bronze Age, an extension of the cultural landscape in the form of terraces towards the village of Vnà can be seen (Raba 1996, 71). This did not change during the Iron Age, but evidence from the Roman Period is rather scarce and only one Roman charcoal fragment was found in a profile (Raba 1996, 71). The last fire traces stem from the Medieval Period with the exception of one trace from the Modern Era (Raba 1996, 71). This evidence points to the repeated use of fire for clearing the areas that were used for agricultural purposes, although these areas would soon have been reforested (Raba 1996, 71).

2.3.3. Terrace types

Raba (1996) structures the terraces into 6 types, of which the first three are morphologically relevant for the purpose of this thesis, although types one and three differ only in their locations, not their morphology. For this reason it was decided to differentiate only between the two first types defined by Raba (1996) in this thesis. These two types are summarised in table (table i).

Terrace Type	Inclination of terrace flat	Inclination of terrace slope	Location	Characteristics	Present-day usage
1	More than 20%	40-100%	Near the present-day villages.	Very clear slopes. These are either fortified by dry walls or overgrown by grasses. The slopes are not regularly mown.	Regularly used as grassed area.
2	0-15%	20-50%	Further away from the present-day villages, often in higher locations.	Slopes are difficult to distinguish from the flats. Slopes and flats are used for the same purposes.	Flats and slopes are used regularly as grassed areas.

The following two figures, figures v and vi, show examples of the two main morphologically distinct terrace types.



Figure v: Terraces of type one which are still very distinctly visible in today's landscape. The Bronze and Iron Age settlement Ramosch Mottata was located on the prominent hill in the top right of the image ([https://www.archaeologie.uzh.ch/de/prehist/forschung/Projekte/TERRA-\(Terrassenlandschaft-Ramosch-Untereingadin\).html](https://www.archaeologie.uzh.ch/de/prehist/forschung/Projekte/TERRA-(Terrassenlandschaft-Ramosch-Untereingadin).html) [accessed 18.06.2020]).



Figure vi: Two terraces of type two are being examined by participants of the TERRA project. These terraces are much less distinct than the terraces of type one (Jonas Blum).

The two types also prevail in different areas, type one being located in the lower area near the present-day villages and type two is prevalent in higher locations. It was already mentioned in chapter 1.1.2 that the area which this thesis is concerned with can be split into an upper and a lower area, the upper area being much more eroded than the lower area (figure ii). Technically, the area around Vnà is also a part of the TERRA project study area, however, because the terraces around Vnà do not differ significantly from those around Ramosch, it was decided to limit the study area to the landscape towards the east of Ramosch.

The summary in table ii shows that the terraces are diverse in their morphology. This diversity can be problematic for semi-automatic image analysis as characteristics of each type of terrace need to be captured. However, the heterogeneity of the terraces is not the only complication. The landscape also contains a system of drainage and/or irrigation ditches, paths, roads and cattle trails; all linear features that are not easily distinguishable from each other in the field (figure vii), let alone on a LiDAR visualisation. It was already stated in the introduction that GeOBIA seems to be a favourable approach to dealing with such complications and chapter 2.4 will discuss this matter further.



Figure vii: The hillside in the background contains numerous paths and irrigation ditches that are very difficult to differentiate (Jonas Blum).

2.3.4. Future of the terraces

Raba (1996) considered different future scenarios and their meaning for the landscape around Ramosch. She considered that if there were no more subsidies for agriculture and the farmers would be forced to sell their goods on the free market, the consequence would be that many people would be forced to give up their agricultural activity (Raba 1996, 144). This would in turn lead to the reforestation of large parts of the area, with open space remaining only at the foot of the village where the flat terrain would allow for the extensive use of the large fields by only one or two agricultural establishments (Raba 1996, 144).

If tourism was encouraged by the canton and the government, the current infrastructure of hiking trails and hotels would have to be expanded (Raba 1996, 145) and for winter tourism, a chairlift would perhaps have to be built. Of course, this increased infrastructure would lead to the destruction of many existing structures in the landscape. Raba saw the answer to preventing these two destructive scenarios in the combination of existing subsidies and future direct payments to farmers in order to make the agricultural use of the terraces attractive, so that the existing landscape could be maintained instead of conserved, leading to the possibility of “soft” tourism as a further source of income for the local population.

To achieve this goal, it is important to know the rich history of the terraces in order to justify their maintenance. In addition, it is important to have an overview of the landscape in case of future destruction. As was mentioned in chapter 2.1, the semi-automation of image analysis can lead to much faster mapping of archaeological objects, which is crucial in cases like these where the landscape is at risk of being damaged.

2.4. Pixels versus objects

The (semi-)automatic image analysis approaches that were presented in chapter 2.2 can be grouped into pixel-based and object-based approaches. Pixel-based approaches rely on the spectral values of each pixel and with a library of known values associated with the objects of interest, the image can be divided into a series of classes that represent those objects (Davis *et al.* 2019a, 26). One problem with this approach is that in some cases, the pixel values of the objects that are to be detected do not differ sufficiently from the pixel values of the image background

(Zingman *et al.* 2016, 4580), the morphology and geometry of the objects being far better identifiers (Zingman *et al.* 2016, 4581; Lambers 2018, 117).

Geographic object-based image analysis, on the other hand, works by partitioning imagery into meaningful segments and assessing their characteristics on a spatial, spectral and temporal scale which, in turn, creates new GIS-suitable geographic information (Hay and Castilla 2008, 77). The segments are pixel groups or regions that are homogeneous and have additional spectral and spatial information compared to single pixels (Blaschke 2010, 3). Because GEOBIA allows for the incorporation of multiple morphological parameters, it is a well suited method for identifying small, spectrally diverse image objects (Davis *et al.* 2019a, 26) that often express distinctive attributes such as shape, size and spatial organisation (Davis *et al.* 2019b, 167). In addition, the segmentation step reduces the spectral variability (De Luca *et al.* 2019, 1) and creates a more homogeneous basis for the classification step.

In addition to the benefit of incorporating multiple characteristics for the object detection, object-based image analysis methods fare better as soon as the spatial resolution of the image is finer than the typical object of interest (Blaschke *et al.* 2014, 180). Especially for heterogeneous land cover and heterogeneous objects, object-based methods are better suited than pixel-based techniques (De Laet *et al.* 2009, 5663; Sevara *et al.* 2016, 496). Figure viii shows the comparison between manual, pixel-based and object-based detection methods applied to the heterogeneous and linear objects of a hillfort carried out by Sevara *et al.* (2016).

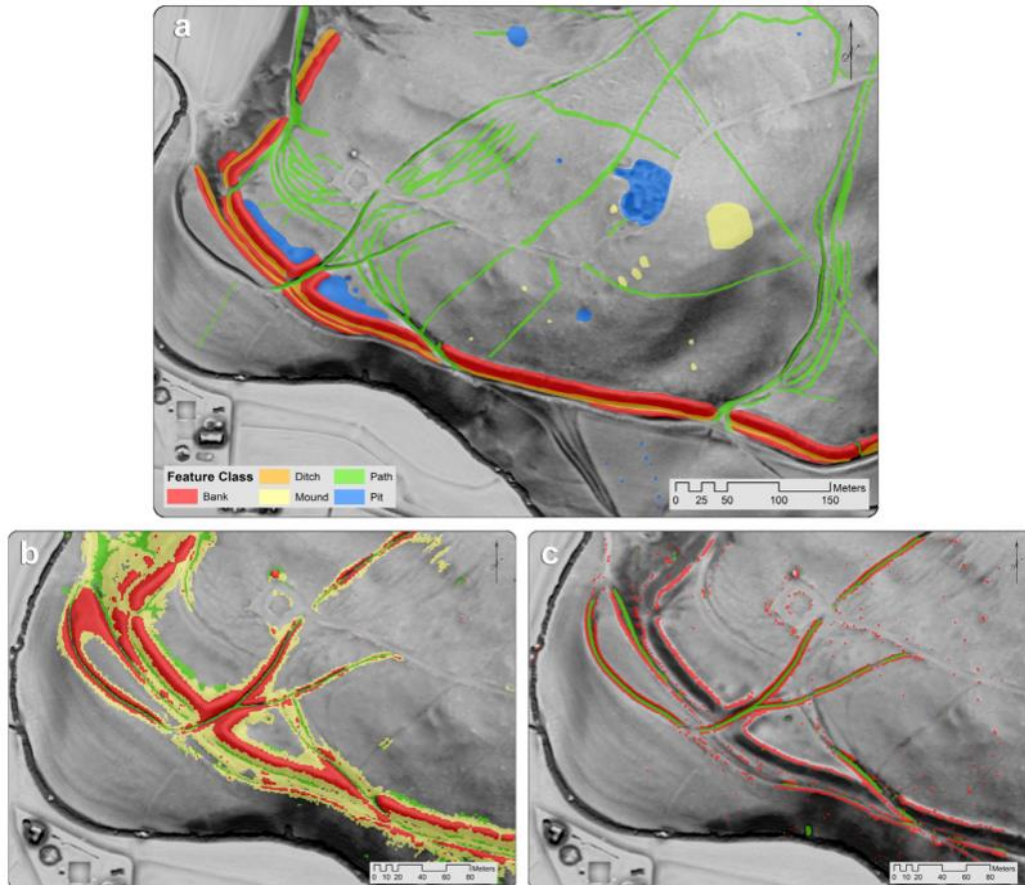


Figure viii: Manual classification of a hillfort (top) compared to object-based methods (left) and pixel-based methods (right) (Sevara et al. 2016, 49).

Gu *et al.* (2017) sum up the benefits of GeOBIA in comparison to pixel-based analyses as follows:

“GEOBIA has the advantages of having a high degree of information utilization, high degree of data integration, high classification precision, and less manual editing (Gu *et al.* 2017, 1).”

Because of the above mentioned advantages, but also because the terraced landscape of the Lower Engadine is comprised of numerous heterogeneous objects, it was decided to develop a GeOBIA workflow.

2.5. Conclusion

There is great need for semi-automatic image classification solutions due to the rapid increase of more and more complex remote-sensing data. While there are still voices of concern about the complete replacement of human interpreters by computer algorithms that lack the flexibility and expert knowledge of humans, there are many benefits to the semi-automation of the image analysis process such as less bias and faster processing speeds. It has to be emphasised that the goal is not to

replace, but rather to support human interpreters, so critics need not fear their complete replacement by machines.

There are many different (semi-)automatic object detection methods, but in this case, Geographic Object-Based Image Analysis (GeOBIA) was chosen as the method of choice because studies such as the one conducted by Sevara *et al.* (2016) show that object-based image analysis methods fare better than pixel-based methods when it comes to heterogeneous landscapes containing linear objects. The study area to which the developed workflow of this thesis is applied is the terraced landscape of the Lower Engadine in the Swiss Alps, and this area contains many heterogeneous and linear objects such as agricultural terraces, irrigation/drainage ditches and roads.

The next section will provide a detailed theoretical overview of GeOBIA in order to provide the reader with the necessary background before going into the more practical parts of the workflow development.

3. Introduction to GeOBIA

This section will take a closer look at Geographic Object-Based Image Analysis (GeOBIA) as a method. In addition to this methodological introduction, the history and evolution of GeOBIA as well as the aims and the potential of this method will be presented, before discussing some current issues of this field. This methodological introduction will further illustrate some of the choices that were made in the context of this thesis, such as the decision that the developed workflow (chapter 5) should only make use of free and open-source software.

3.1. Terminology, history and evolution of GeOBIA

Around the year 2000, the first commercial software specifically for image segmentation and classification as opposed to the analysis of individual pixels appeared (Blaschke *et al.* 2014, 180). Due to the shift from pixel-based to object-based image analysis, the authors Hay and Castilla proposed a new name for object-based image analysis, as they observed the necessity of an ontology with a common language and understanding of the new paradigm (Hay and Castilla 2008, 76). The two researchers state that:

“[...] we formally propose *Geographic Object-Based Image Analysis* (GEOBIA - pronounced *ge-o-be-uh*) as the name of this new paradigm. We further propose that a worldwide GEOBIA community needs to be fostered so as to rapidly facilitate the scrutiny and dissemination of new and evolving related principles, methods, tools and opportunities. (Hay and Castilla 2008, 76).”

Thus, a new and internationally recognized name for a prospering paradigm was created. The Ge(o) pseudo prefix was added to the existing OBIA name in order to place an emphasis on the geographic components of object detection (Hay and Castilla 2008, 79). Hay and Castilla defined GeOBIA as a sub discipline of GIS, as the resulting classified image objects offer new geographic information that comes in a GIS-suitable format (Hay and Castilla 2008, 77). The authors note that GeOBIA acts as a bridge between GIS and remote sensing data, as the remote sensing images come in a raster format, and these are linked to the predominantly vector domain of GIS through the classified image object polygons (Hay and Castilla 2008, 77).

3.2. Methodology

To summarise once more; GeOBIA requires image segmentation, attribution, classification and the possibility to link objects in space and time (Hay and Castilla 2008, 77). The segmentation step clusters pixels into regions, which are sets of

connected pixels from which image objects can be extracted (Derivaux *et al.* 2010, 2364; De Luca *et al.* 2019, 1). Representative segments are then assigned a training class, which is in turn used to classify the entire image. Ideally, the segments possess an intrinsic size, shape and geographic relationship with the real world features that they represent (Blaschke *et al.* 2014, 185). However, the segments are not always meaningful, which means that they do not always correspond to real world features straight away (Magnini and Bettineschi 2019, 11). This is why further refinement is needed and segmentation and classification are iterative steps (Magnini and Bettineschi 2019, 11). Figure ix shows the iterative nature of segmentation and classification. The aim of this repeated segmentation and classification is to generate segments that correspond to image objects which fulfil the major criteria of the intended classes (Blaschke *et al.* 2014, 187). Image objects as defined by Castilla and Hay (2008) are regions within a digital image that are internally coherent as well as different from their surroundings and potentially represent geo-objects (Castilla and Hay 2008, 108), which in turn, are real-life geographical objects on or near the surface of the Earth (Castilla and Hay 2008, 98). These definitions are not to be confused with the distinction between objects and features as defined within the field of computer vision, where properties of an image are defined as features and real-world entities are defined as objects (Traviglia *et al.* 2016, 14). Within this thesis, the author has opted for the terminology defined by Castilla and Hay (2008).

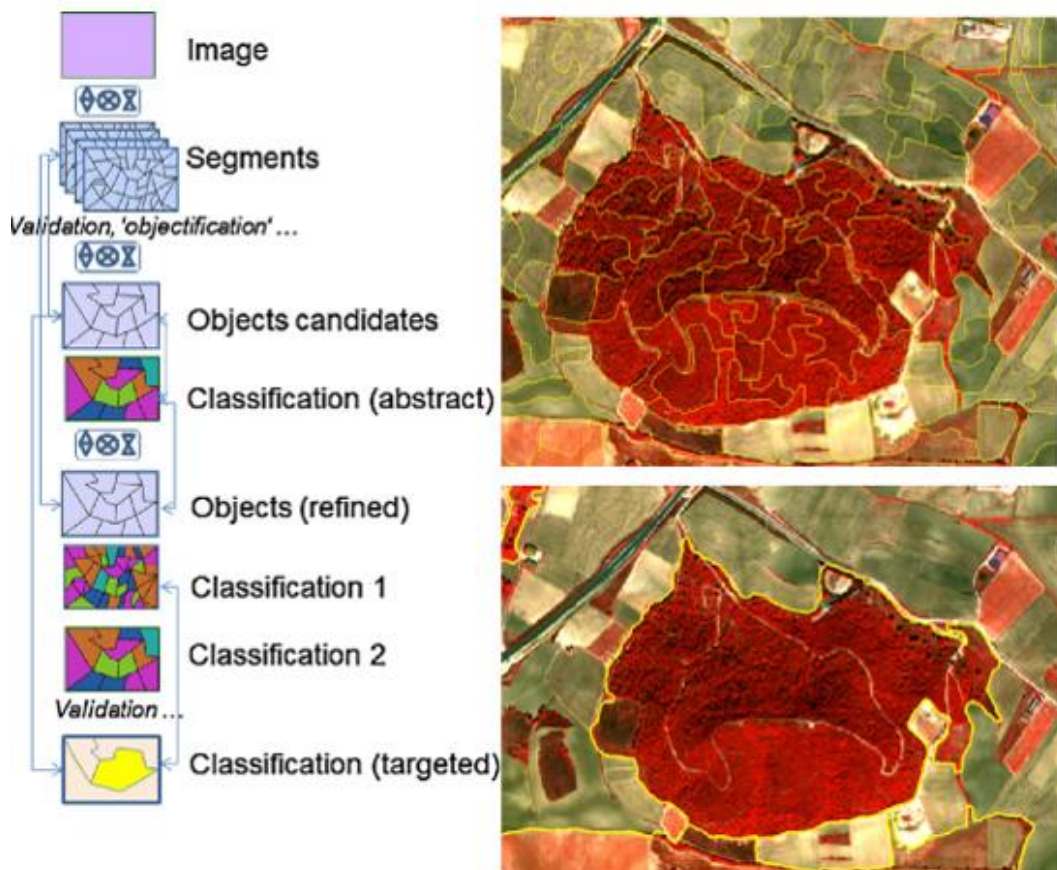


Figure ix: The iterative segmentation and classification steps until the image objects correspond to the desired geo objects (Blaschke et al. 2014, 186).

In the following sub chapters, the different segmentation algorithms, as well as the classification approach will be discussed.

3.2.1. Segmentation

Segmentation divides an image into regions or segments that are spatially continuous, disjoint and homogeneous or, in other words, the internal heterogeneity of a segment should be less than the heterogeneity of the segment's neighbouring regions (Blaschke *et al.* 2014, 186). The heterogeneity criterion can be manually adjusted (Magnini and Bettineschi 2019, 11), thus creating smaller or larger segments. Ideally, the segmentation should return regions that correspond to the image objects in order to allow for an accurate classification (Derivaux *et al.* 2010, 1; Hossain and Chen 2019, 116).

3.2.2. Overview of segmentation algorithms

Traditional segmentation methods can be grouped into pixel-based, edge-based and region-based approaches (Blaschke *et al.* 2014, 186).

Pixel-based segmentation involves searching for homogeneous objects within the image by applying global threshold operations to combine pixels that possess similar values (Schiewe 2002, 81; Hossain and Chen 2019, 116). Figure x shows a schematic drawing of the thresholding process. The resulting components that each possess similar values are then grouped to a region (Schiewe 2002, 81; Hossain and Chen 2019, 116). This approach is less suitable for the analysis of remotely sensed data due to varying values of objects depending on their placement within the real world or image (Schiewe 2002, 81; Hossain and Chen 2019, 116). Additionally, there is no consideration of the neighbourhood relationships between the resulting regions (Schiewe 2002, 81), and it is precisely these relationships that make GeOBIA such a powerful tool. This aspect will be discussed further in chapter 3.2.3. Pixel-based segmentation is thus unsuitable for GeOBIA (Hossain and Chen 2019, 116) and will not be further discussed in this thesis.

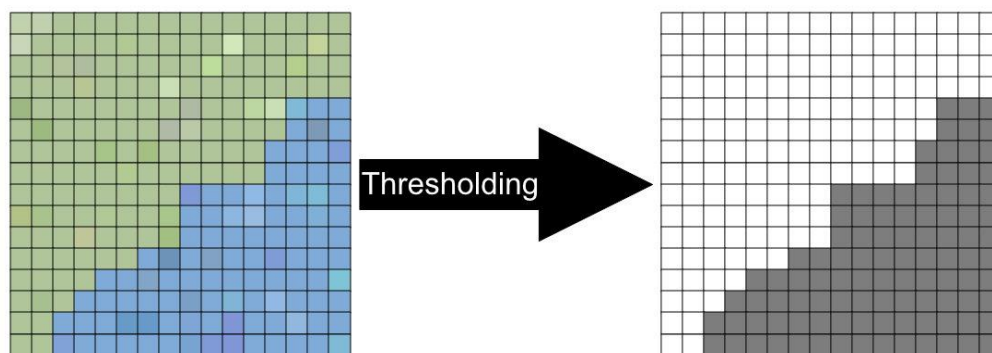


Figure x: Schematic drawing of a pixel-based segmentation (Pierina Roffler).

Edge-based approaches identify edges which are then contoured with a contouring algorithm. Edges are regarded as boundaries between objects and are located in areas where pixel properties change abruptly (Hossain and Chen 2019, 117). After the edges are successfully identified, the next step is transforming them into closed boundaries, a step which involves connecting the gaps at places where no edge is detected, joining those edge parts that make up a single object but also excluding those edges that are produced by image noise (Hossain and Chen 2019, 117). The most popular edge-based segmentation method is the Watershed Transformation (Hossain and Chen 2019, 117), although the researchers comment that the Watershed Transformation may also be considered a region growing algorithm. This algorithm simulates the flooding of the image and then transforms the image

into a gradient that indicates objects with a topographical surface (Hossain and Chen 2019, 117). Figure xi shows a schematic drawing of a watershed segmentation. Watershed is only one of many different edge-based segmentation methods, and unfortunately all available operators create broken edges or miss some essential edges (Hossain and Chen 2019, 117).

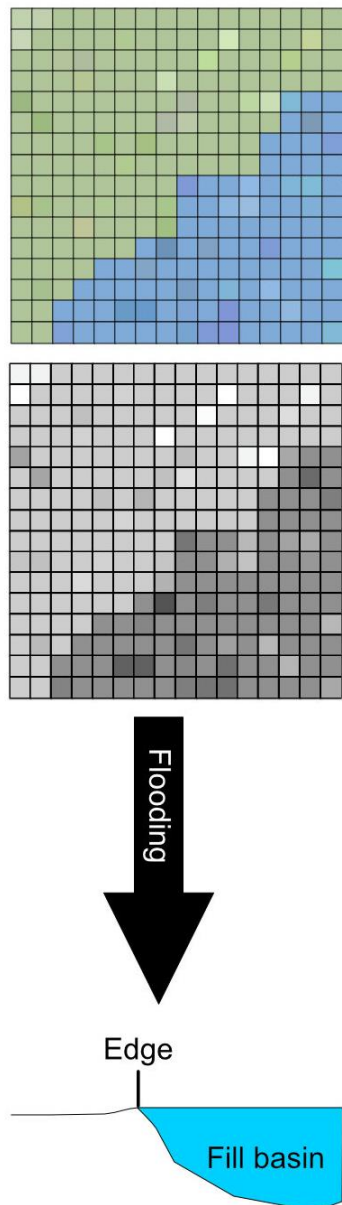


Figure xi: Schematic drawing of a watershed segmentation (Pierina Roffler).

Region-based algorithms start from the inside of an object until meeting the object boundaries as opposed to the edge-based methods that define the boundaries first and then the object (Hossain and Chen 2019, 117). The size of the region depends on the selection of the homogeneity criterion by the user (Hossain and Chen 2019,

119). The regions can either be generated with a top-down approach of splitting the image into homogeneous regions or with the bottom-up approach of region growing (figure xii) which combines pixels into homogeneous regions from a starting point or “seed” (Hossain and Chen 2019, 119).

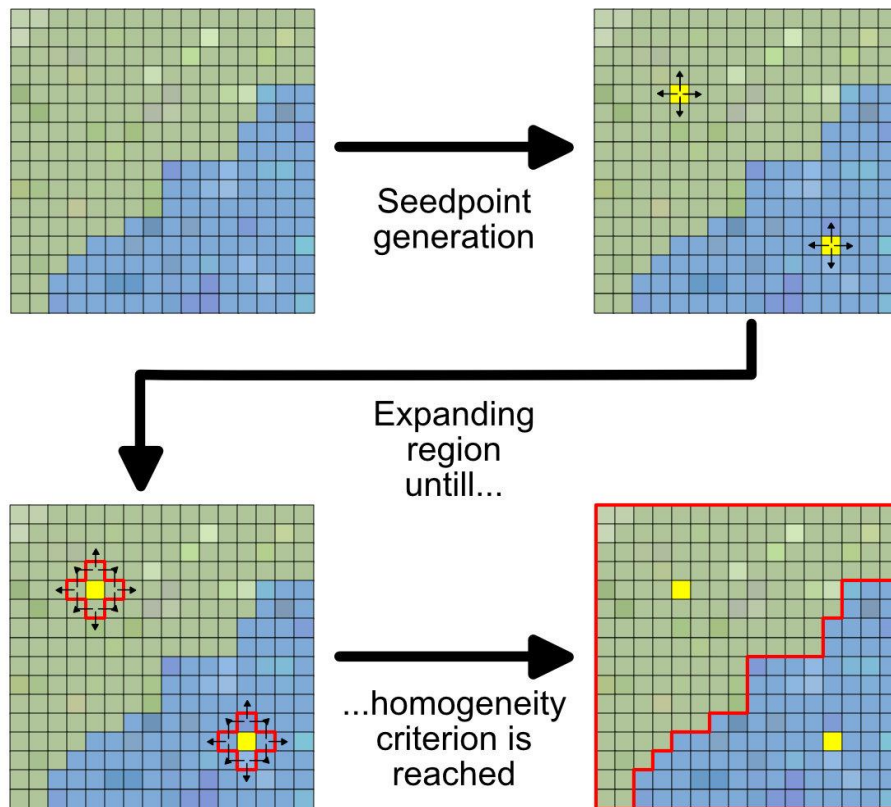


Figure xii: Schematic drawing of a region growing segmentation (Pierina Roffler).

Hybrid methods first outline initial segments using edge-based methods and then merge them using region-based methods (Hossain and Chen 2019, 122). This means that both the boundary pixels and the internal pixels of the objects are used, the first to create the initial segments and the latter to merge similar segments (Hossain and Chen 2019, 122).

Edge-based segmentation algorithms are less complicated than region-based algorithms and work well with images with a high contrast between objects and background (Hossain and Chen 2019, 122). As soon as the images have smooth transitions, low contrast or too much noise, edge-based algorithms run into problems (Hossain and Chen 2019, 123). High-resolution or multi-spectral images make edge detection very complicated due to excessive texture or inconsistent locations of edges in multiple bands (Hossain and Chen 2019, 123).

Region-based methods are less sensitive to noise compared to edge-based approaches, generate spatially and spectrally homogeneous segments and can produce segments at multiple scales (Hossain and Chen 2019, 123). This method also allows the user to incorporate multiple criteria for the segmentation at the same time, as well as allowing the selection of seed points and merging criteria individually (Hossain and Chen 2019, 123). On the other hand, region-based methods are more complicated and time-consuming and finding the right parameters is challenging (Hossain and Chen 2019, 124).

Hybrid methods generate better results than edge- and region-based techniques alone, but they are difficult to implement, computationally heavy and there is no readily available software on the market yet (Hossain and Chen 2019, 124).

3.2.3. Semantic, hierarchical classification

Once the image is segmented in such a way that the segments correspond to the image objects, they can be classified either by selecting training areas and feeding them to a classifier algorithm or by means of direct evaluation performed by the analyst (Magnini and Bettineschi 2019, 11). Direct, manual evaluation generally outperforms the method of feeding training areas to a classifier, but the selection is subjective and cannot be used for the creation of exportable rule-sets (Magnini and Bettineschi 2019, 11). Because the developed workflow should ideally be applied to other areas than the specific case study in this thesis, manual evaluation is not an option.

One of the benefits of GeOBIA as compared to pixel-based approaches is that multiple scales within one image can be addressed (Blaschke *et al.* 2014, 187) depending on the desired object classes (figure xiii).

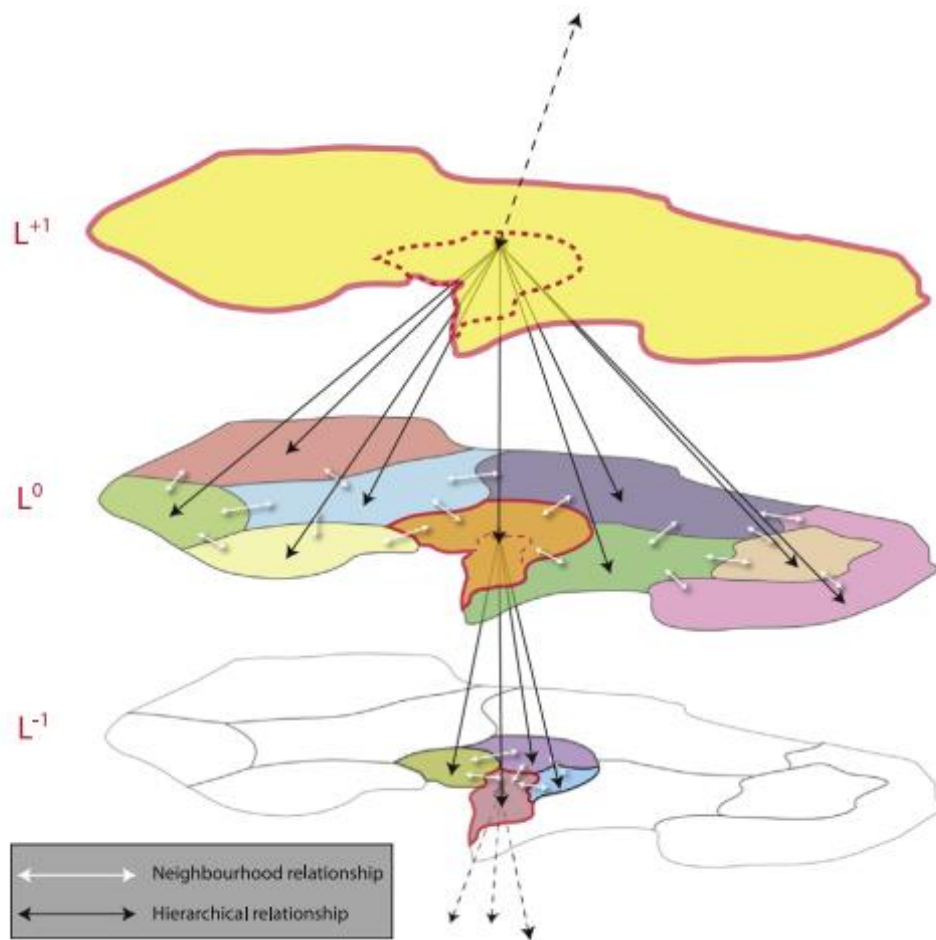


Figure xiii: The relationships (hierarchical and neighbourhood) of different image objects at different scales (Blaschke *et al.* 2014, 187).

The hierarchical and neighbourhood relationships between image objects allow GeOBIA to translate the characteristics of image objects to real world features by using so called semantics based on descriptive criteria and the expert knowledge of the analyst (Blaschke *et al.* 2014, 188). These semantics are used to describe the association between adjacent pixels (De Luca *et al.* 2019, 8) but also the hierarchical networks between image objects (Blaschke *et al.* 2014, 185). Such neighbourhood and hierarchical relationships between segments are a big advantage of GeOBIA, which is why pixel-based segmentation methods are unsuitable for GeOBIA as they cannot consider such relationships (chapter 3.2.2). Sevara and Pregesbauer (2014) illustrate the hierarchical and neighbourhood relationships using a hillfort as an example (Figure xiv).

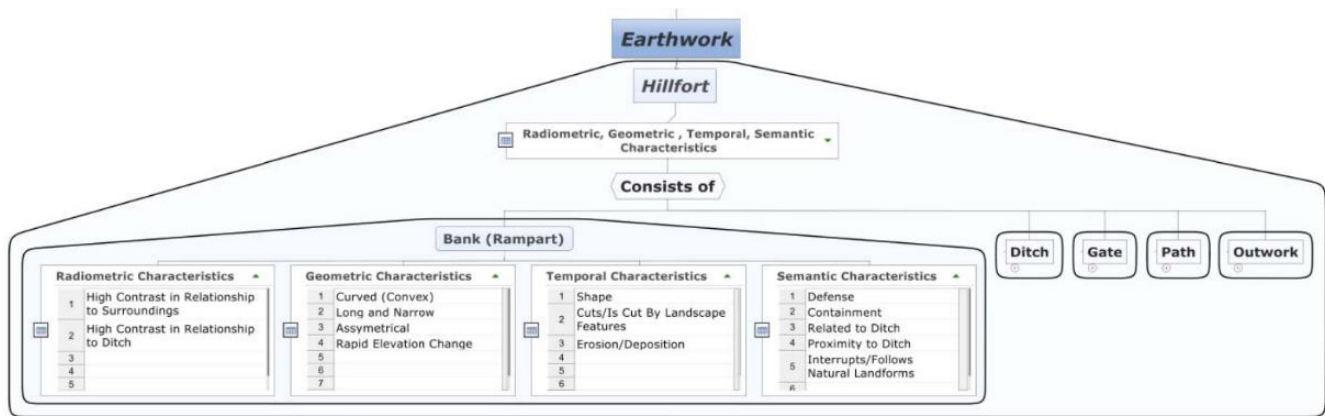


Figure xiv: The concept of semantics and hierarchies explained on the basis of a hillfort (Sevara and Pregesbauer 2014, 141).

This example shows that hillforts are a type of earthwork and consist of banks, ditches, gates etc. These subclasses possess different geometric, radiometric or temporal characteristics and are connected to each other by semantics such as “proximity to...”, “contained by...” and others. Semantics of the agricultural terraces of the Lower Engadine would be that each terrace is composed of a terrace flat, a terrace edge and a terrace slope, the edge being located directly in between a flat and a slope. These semantics were very helpful for the development of the final workflow, which will be presented in chapter 5.

3.3. Current Issues

3.3.1. FOSS

A large number of GeOBIA research projects have made use of proprietary software such as eCognition by Trimble (for example: Csillik 2017; Davis *et al.* 2019a; Davis *et al.* 2019b; Freeland *et al.* 2016; Gu *et al.* 2017; Jahjah and Ulivieri 2010; Meyer *et al.* 2019; Sevara *et al.* 2016). However, there is a growing interest in open source alternatives as FOSS (Free Open Source Software) applications are not only free of charge, but also have the benefit of an open source code (Ducke 2012, 571), the algorithms of which can be interrogated and adapted to suit the needs of the project (Ducke 2012, 572; De Luca *et al.* 2019, 3). Additionally, newer algorithms are often available online before being published for those users who are willing to use a development version of the software (De Luca *et al.* 2019, 3).

Knoth and Nüst (2017) remark that until recently, the term “reproducible” in GeOBIA was used to describe the shift from manual analysis to semi- and automatic analysis using clearly defined processing steps and classification criteria (Knoth

and Nüst 2017, 2). However, in order to be fully reproducible, access to the data and source code, as well as ease of use and the customizability of methods is required (Marwick *et al.* 2017, 17, Knoth and Nüst 2017, 1), and these criteria do not apply to proprietary software such as eCognition. In summary, FOSS promotes the reuse, improvement and adaptation of a methodology or software (Knoth and Nüst 2017, 2).

An additional functionality of FOSS is that these programmes can be combined with each other in a sequential workflow. This means that each individual software can contribute to a part of the workflow following the philosophy that each programme should provide only the specific feature that it excels at (Knoth and Nüst 2017, 2).

It is for the above mentioned reasons that this thesis will make use only of FOSS applications and combine the suitable ones with each other.

3.3.2. Segmentation parameter selection

The most criticized step of GeOBIA projects is the segmentation, as this step is highly dependent on the personal choices of the analyst (Magnini and Bettineschi 2019, 12). The segmentation quality also has a direct influence on the image classification that bases on it (Cheng and Han 2016, 16). Often, the selection of the segmentation scale parameters is reliant on trial-and-error methods, which are mainly based on a subjective visual assessment by the analyst (Cheng and Han 2016, 16; De Luca *et al.* 2019, 10). These decisions allow flexibility and the incorporation of expert knowledge, however, it also means that the decision process is not easily reproducible which runs against the argument that GeOBIA is an unbiased classification tool (Cheng and Han 2016, 16).

Because the segmentation step is iterative and often based on trial-and-error, frequently an under- or over segmentation occurs (Derivaux *et al.* 2010, 2364; Sevara *et al.* 2016, 488). Under segmentation occurs when the segment spans over multiple object classes, leading to the misclassification of some parts of the segment, an error, which cannot be corrected in the classification step (Derivaux *et al.* 2010, 2364). Over segmentation occurs when an object is covered by many segments, which leads to the extracted attributes being far less representative of the object class and producing a lower quality result (Derivaux *et al.* 2010, 2364). Over

segmentation is usually better than under segmentation and especially in archaeology, an apparent over segmentation is often necessary in order to deal with the secondary traces within an object class (ie. crop marks within an agricultural field; Magnini and Bettineschi 2019, 12). Given the heterogeneous nature of archaeological features, choosing appropriate segmentation parameters is very challenging (Cheng and Han 2016, 16; Derivaux *et al.* 2010, 2364).

Some attempts have been made at developing tools that can detect suitable segmentation scale parameters. One such example is the Estimation of Scale Parameters (ESP) tool, developed by Drăguț *et al.* (2010), that estimates suitable scale parameters for a multiresolution segmentation and carries out said segmentation automatically (Drăguț *et al.* 2010, 861). Unfortunately, this tool is implemented in Trimble eCognition and thus does not meet the criterion set by this thesis that the proposed GeOBIA workflow should make use only of free and open-source software.

3.4. Objectives and Potential

Hay and Castilla defined the primary objective of GeOBIA as a discipline as follows:

“[...] to develop theory, methods and tools sufficient to replicate (and/or exceed experienced) human interpretation of RS images in automated/semi-automated ways. This will result in more accurate and repeatable information, less subjectivity, and reduced labor and time costs (Hay and Castilla 2008, 80).”

It is important to note that it was never the objective of these new technologies to replace a human interpreter, but rather to be an aid. As Blaschke *et al.* note, the potential of human vision remains to be achieved (Blaschke *et al.* 2014, 185), and the archaeologist remains an essential part of the whole segmentation, classification and interpretation workflow (Magnini and Bettineschi 2019, 13).

The final phase of a GeOBIA workflow should always be the systematic validation of the results (Magnini and Bettineschi 2019, 16). Following this validation step, the verified rulesets can be exported and applied in different contexts such as a new case study (Magnini and Bettineschi 2019, 16). It is also the goal of this thesis to come up with a reproducible workflow that can be applied to or modified to fit other case studies by other researchers as needed.

GeOBIA has been called a new and evolving paradigm (Blaschke *et al.* 2014, 189) that can increase the efficiency of an interpretation significantly (Sevara *et al.* 2016, 496). As Hay and Castilla (2008) noted, GeOBIA provides a way to create geointelligence as opposed to simply collecting images (Hay and Castilla 2008, 80).

3.5. Conclusion

The term GeOBIA was proposed in the year 2008 when Hay and Castilla observed the need of an ontology with a common language and understanding of a new paradigm (Hay and Castilla 2008, 76). The Ge(o) prefix was chosen in order to place an emphasis on the geographic components of object detection (Hay and Castilla 2008, 79). GeOBIA requires image segmentation, attribution and classification. There are several different possible segmentation approaches: pixel-based, edge-based, region-based and even hybrid methods that combine different approaches. Each of these methods comes with its own set of benefits and drawbacks that were discussed in chapter 3.2.2. The selection of segmentation parameters is essential to the success of the classification, and the choice of these parameters is determined by the user. A benefit of GeOBIA is that image objects not only possess hierarchical, but also neighbourhood relationships with other objects, making their classification very intuitive and versatile. GeOBIA has a huge potential, especially in the case of heterogeneous and linear objects such as those to be classified in the study area of this thesis.

After this more theoretical chapter, the next chapter takes a look at different FOSS applications for GeOBIA that contain a Graphic User Interface (GUI). A GUI is necessary in order to promote accessibility and reproducibility of the final workflow because many current archaeologists do not have a background in programming and it cannot be expected of them to write their own algorithms.

4. Testing existing software solutions with a GUI

As mentioned in chapter 1.2, the first aim of this thesis was to provide an overview of existing open source GeOBIA software solutions and to assess the user friendliness and effectiveness of each programme. As most archaeologists do not have a background in programming and thus may find it difficult to develop their own algorithms, it is important to find common ways for publishing rule-set libraries (Magnini and Bettineschi 2019, 11), and to have easily accessible, effective software with a Graphical User Interface (GUI). In order to promote accessibility and reproducibility, the trend should go in the direction of FOSS rather than proprietary software.

The first research question that is to be answered in this subsection is the following: Is there an open source solution for GeOBIA available with a Graphical User Interface (GUI) that is user friendly, does not require additional coding and will prove through systematic testing to be capable of classifying the heterogeneous and linear features within the terraced landscape of the Lower Engadine? In order to answer this question, a number of FOSS software was tested by the author. For the purpose of limiting the number of tested software to a certain extent, the FOSS applications that are summarised by Hossain and Chen (2019) in table 4 (Hossain and Chen 2019, 124) were used as a reference.

The added benefit of this software testing phase was that it became apparent which visualisations work best for the different areas of the research project, but also which elements an effective GeOBIA workflow needs to comprise of. In order to understand why the large part of research papers covering GeOBIA today still make use of proprietary software rather than FOSS solutions, two popular proprietary solutions were also tested.

4.1. Test criteria and process

The setup of the testing process was very straightforward. The author downloaded the respective programmes and consulted the available training material. From this starting point, the author performed a GeOBIA on a LiDAR visualisation and reflected on the process. At this stage it was not the aim to achieve the best classification results possible, but rather to get to grips with the different options and functionalities before deciding which ones to incorporate into the workflow. The criteria for these tests were the following:

- User friendliness – Is the software well documented and is there training material available or an active forum where a user can get help?
- Suitability – Can the software handle the single band LiDAR visualisations used in this thesis?
- Effectiveness – Is there a possibility for incorporating hierarchical or neighbourhood relationships?

In the following section, the results are summarised first for the proprietary software and subsequently for the FOSS solutions.

4.2. Proprietary software

4.2.1. Trimble eCognition

Trimble eCognition offers a free developer trial that is fully functional but does not allow any projects to be saved or any rulesets to be exported.³ Nevertheless, this trial version was suitable for the purpose of getting a feel for the programme and for testing its functionalities.

The most straightforward GeOBIA workflow uses a segmentation algorithm and the subsequent selection of meaningful segments as training data for a classifier. For the selection of training segments, eCognition offers a classification sampler option rather than editing the values in the segment attribute table. With this option, if a class is active, the segments can be selected by double clicking on them and their values are stored. Two segmentation algorithms were tested; Watershed and Multiresolution segmentation, and the latter was found to produce segments that much more closely followed the image objects. Overall, the workflow is effective but not very intuitive due to the software interface (figure xv) and functionalities being very unique and thus, quite a bit of time needs to be invested into getting to know the programme.

³ <https://geospatial.trimble.com/ecognition-trial> [accessed 13.05.2020]

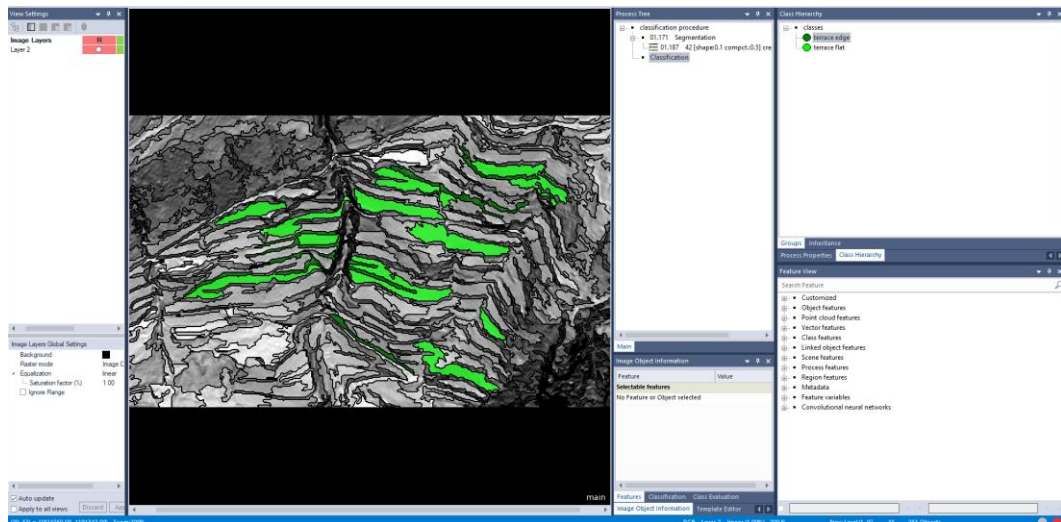


Figure xv: Screenshot of the interface of Trimble eCognition during the selection of training segments.

It has to be said at this point that eCognition offers a vast amount of additional functionalities for GeOBIA, including the option of adding class hierarchies and including geosemantics for classification, but testing and understanding them all would have gone beyond the scope of this thesis.

4.2.2. ERDAS IMAGINE

ERDAS IMAGINE is a proprietary software by Hexagon Geospatial.⁴ The team from IMAGEM, Hexagon’s partner for the Benelux market, kindly provided the author with a free one month trial after being informed about this thesis project. ERDAS IMAGINE is much more intuitive to use than Trimble eCognition. The GUI strongly resembles that of other popular software such as Autodesk’s AutoCAD (figure xvi) and thus was very easy to get to grips with. Additionally, there is an eTraining library that contains all sorts of tutorials⁵ as well as an active community⁶.

⁴ <https://www.hexagongeospatial.com/brochure-pages/erdas-imagine-brochure> [accessed 07.05.2020]

⁵ <https://community.hexagongeospatial.com/t5/IMAGINE-eTraining/tkb-p/eTERdasImagine> [accessed 07.05.2020]

⁶ https://community.hexagongeospatial.com/t5/IMAGINE-Discussions/bd-Discussions_KS_ERDAS_IMAGINE [accessed 07.05.2020]

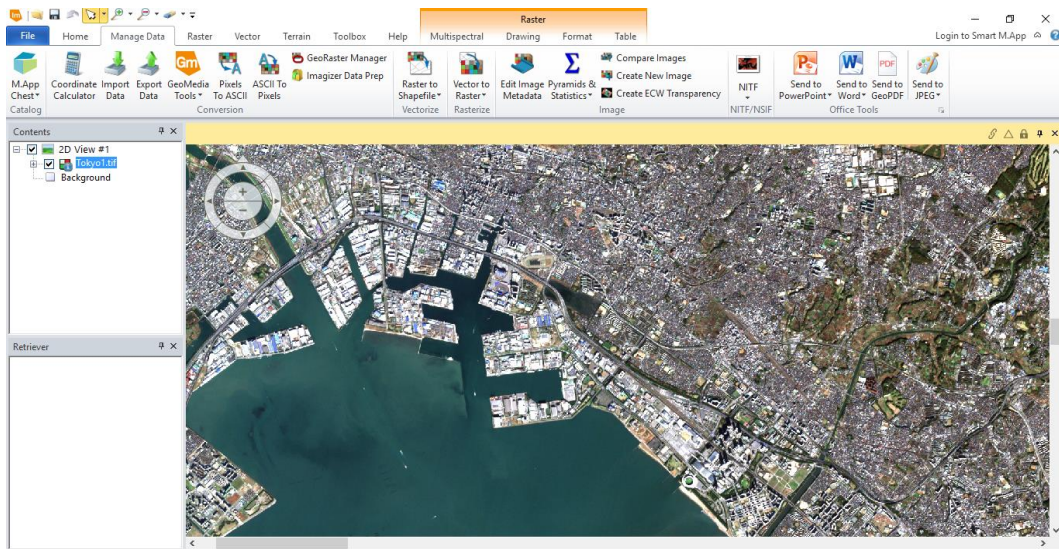


Figure xvi: The GUI of ERDAS IMAGINE that resembles the GUI of Autodesk's AutoCAD (<https://gisgeography.com/wp-content/uploads/2016/07/ERDAS-Imagine-Tokyo.png> [accessed 17.06.2020]).

There is the option of a supervised classification with the help of Region Of Interest (ROI) polygons created by the user. However, the lack of a segmentation step means that these types of workflows are not strictly speaking GeOBIA. ERDAS IMAGINE also offers a tool for seeded region growing. With this tool, the user can select a pixel which will act as the starting point (or “seed”) for a region growing algorithm. The user can define the size of the resulting region with the help of a slider, and the region is adjusted automatically. These regions are added to the signature editor and once a few regions of a class have been grown, they can be combined to one signature. The resulting signature adopts the average of all the values of grown region of a class. Finally, these class signatures are used as training data for a supervised classification algorithm. Figure xvii shows the ERDAS IMAGINE GUI after region growing and merging the class statistics.

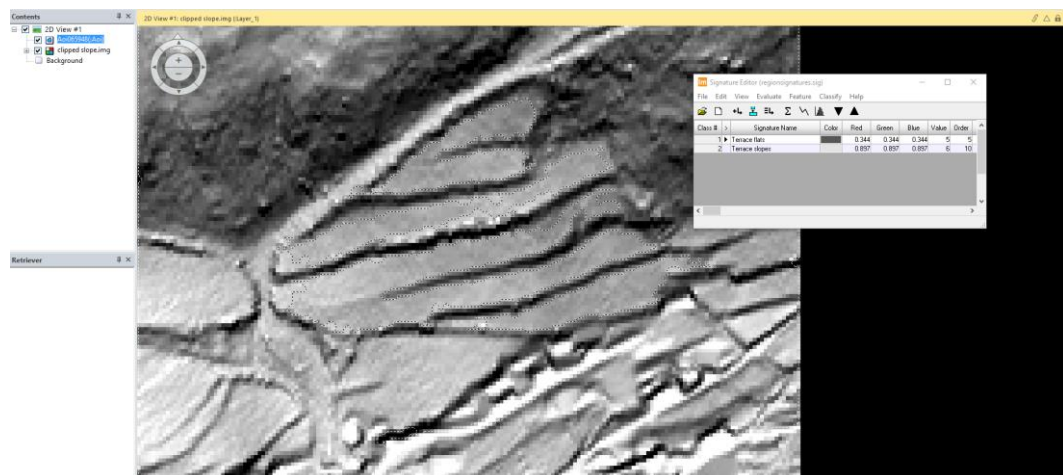


Figure xvii: Screenshot of the ERDAS IMAGINE GUI after region growing and merging the class signatures.

All in all, ERDAS IMAGINE is an intuitive software and the workflow is easy to use and easy to understand, especially for someone who is only at the beginning of getting to grips with GeOBIA. There are many places one can turn to for help, but then again, this is the type of support that users are paying for.

4.3. FOSS

4.3.1. SAGA GIS

The first FOSS software to be tested was SAGA GIS (Conrad *et al.* 2015). SAGA stands for System for Automated Geoscientific Analyses and is a GIS that has a number of image processing algorithms as well as an intuitive GUI to enhance user friendliness. It is also FOSS, which in this thesis is the main criterion for the selection of existing GeOBIA solutions. It was developed by a team of researchers at the department of Physical Geography, University of Göttingen in the early 2000s. On the SAGA website, it is stated that the main developers were working together on several research projects in the late 1990s and were a very heterogeneous group of people with regard to their preferred operating systems, programming languages, development environments and data formats.⁷ This highlighted the need for a common platform and the idea for SAGA was born. SAGA offers a wide range of data analysis tools for raster as well as for vector data and terrain analysis is a strength of SAGA (Conrad *et al.* 2015, 1992).

SAGA offers a number of tutorials online, both in written form as well as on YouTube. Fisher *et al.* developed the tutorials regarding satellite image and terrain analysis and these tutorials can be accessed online (<https://sagatutorials.wordpress.com/>), but can also be found on YouTube (eg: “Supervised OBIA SAGA-GIS”⁸) and in the form of a print publication (Fisher *et al.* 2017). It was precisely because SAGA is documented so well that it was chosen as the first FOSS solution to be tested.

In terms of GeOBIA, SAGA offers a very useful seeded region growing algorithm called “Object Based Image Segmentation” as the first segmentation step. A number of parameters can be changed but keeping all the default values and changing only the bandwidth for seedpoint generation led to useful segmentation

⁷ <http://www.saga-gis.org/en/index.html> [accessed 13.05.2020]

⁸ https://www.youtube.com/watch?v=584nexgW_z8 [accessed 06.05.2020]

results. What is very useful in SAGA is that the results are overwritten straight away if the input images stay the same and a variable is changed, meaning that the user does not need to reimport and restyle the segments each time new values are tested. This leads to quick and easy assessment and adaptation of the segments and a meaningful segmentation can be achieved very quickly. The next step is opening the attribute table of the segmentation layer and adding a new column for the training data. Next, meaningful segments can be selected and their classes added to this newly created training data column. The final step is the classification. In SAGA, the tool “Supervised Classification for Grids” can be used in order to input the image that is to be classified as well as the segments containing the training data. Figure xviii shows the SAGA GUI after performing a supervised classification for grids on a Sky View Factor visualisation. As class identifier, the training data column must be selected, and finally, one can chose from a number of classifiers.

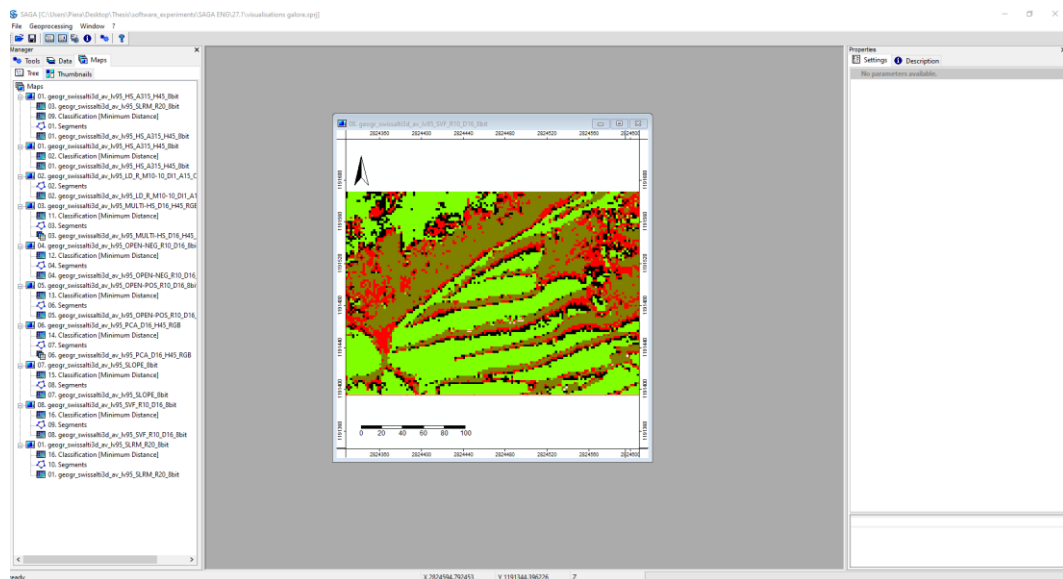


Figure xviii: Screenshot of the SAGA GUI after performing a supervised classification for grids on a Sky View Factor visualisation.

Each of these steps are easy to work with and their implementation takes only a few seconds. This made the iterative nature of segmentation and classification in SAGA very easy. Generally it can be said that SAGA is incredibly easy to work with, especially compared to some of the other tested FOSS software. It is a GIS that anyone who has worked with ArcGIS or QGIS will find intuitive and the detailed documentation and range of tutorials make learning the specifics a manageable task.

4.3.2. QGIS

QGIS (QGIS.org, 2020) is a FOSS GIS that was initially designed in 2002 to provide a GIS data viewer. Since then the project has grown substantially and today, QGIS is used by many for their daily GIS needs (QGIS Development Team 2020, 3). QGIS supports a number of raster and vector formats and was deemed a promising platform for this thesis as it offers the possibility of using different plugins and even combining algorithms from different toolboxes. Additionally, it was the hope that the graphical workflow modeller would offer the possibility of semi automating the developed workflow in order to further promote its ease of use. The author used QGIS 3.4 Madeira. Two plugins were selected to be tested in QGIS; the Orfeo Toolbox (OTB) and the Semiautomatic Classification Plugin (SCP). OTB is among the GeOBIA solutions listed by Hossain and Chen (2019), SCP was discovered in the QGIS plugin library during the installation of the OTB plugin.

4.3.2.1. Semi-automatic classification plugin (SCP)

The semi-automatic classification plugin (SCP) was developed by Luca Congedo and is a FOSS plugin for QGIS that allows semi-automatic classification of remote sensing images (Congedo 2016, 1). It also provides tools for the download of remote sensing imagery that are free of charge, pre-processing, post-processing, as well as raster calculation (Congedo 2016, 1). In the most recent documentation, Congedo states that:

“The overall objective of *SCP* is to provide a set of intertwined tools for raster processing in order to make an automatic workflow and ease the land cover classification, which could be performed also by people whose main field is not remote sensing (Congedo 2016, 1).”

The use of the plugin truly is very straightforward and intuitive. The documentation contains several tutorials, as well as very detailed information to all options (Congedo 2016), and Congedo also has a YouTube channel where he uploads tutorials for SCP such as the “Basic tutorial 1: Land Cover Classification of Landsat Images”⁹.

Once the image is loaded, Regions Of Interest (ROI) can be selected and assigned a class and even a subclass. Figure xix shows the SCP Dock in QGIS with the tab open for selecting ROI of classes. This makes hierarchical classification very

⁹ <https://www.youtube.com/watch?v=fUZgYxgDjjsk&pbjreload=10> [accessed 07.05.2020]

straightforward. In the end, the statistics from the ROI are used in order to classify the entire image. A very handy feature is that the classification results can be shown for the classes as well as the subclasses. Unfortunately, it turns out that the SCP was developed for remote sensing images that contain four bands or more (Congedo 2020, 228), meaning that single band Lidar visualisations are not suitable for this plugin. A workaround for this problem is the duplication of the single band visualisations (Verschoof-van der Vaart *et al.* 2020, 12), however, this additional step means that this plugin is less straightforward and user friendly than other options. Additionally, the lack of a segmentation step means that image classification with the SCP is not strictly speaking a GeOBIA workflow.



Figure xix: Screenshot of the SCP dock with the training input tab open, ready to enter Regions Of Interest (ROI) for different classes.

4.3.2.2. Orfeo Toolbox

Orfeo Toolbox (OTB) is a standalone programme but also a plugin for QGIS. It was created by a core development team in the context of the CNES Pleiades mission, but has since been maintained and expanded by a very large community (Grizonnet *et al.* 2017).

It features an online “cookbook” with information for new users on practical matters such as its installation to use as a QGIS plugin, but also some helpful tutorials or “recipes” that the users can try out.¹⁰ There is also a section in the cookbook that contains descriptions of all the applications.¹¹ It was decided to work with the OTB plugin, version 7.1.0, within QGIS 3.4 Madeira with the possibility of combining different toolboxes in mind. Up until QGIS 3.1, OTB was installed as a default plugin, from 3.3 onwards the user needs to link OTB to QGIS manually. With the help of the cookbook, this was a fairly uncomplicated matter.

The QGIS toolbox contains a four step workflow for a Large Scale Meanshift Segmentation. Step one is image filtering, step two is the segmentation, step three is a region merging process to eliminate segments that are too small and step four is the vectorization of the merged segments. The result is a vector file of the segments not unlike the one generated by SAGA with the Object Based Image Segmentation tool (Chapter 4.3.1). These segments can either be classified directly by adding a training field in the attribute table or merged with the attribute table of training areas. The statistics of each class can be computed and saved in an xml file that can in turn be used to train a Support Vector Machine (SVM) classifier. Unfortunately, the training algorithm is unavailable in OTB 7.1.0.

A drawback of the method with the training polygons is that these polygons can span several segments (figure xx). In this case there are two options; either assign the same class to all segments that are touched by the training polygons, or only assign the class to the first segment that intersects a training polygon. In both cases, some training segments are either left out or assigned to two different classes, leading to classification errors. It is for this reason that the option of training segments directly by adding a training field in the attribute table seems favourable to the author. As for the missing training step for the SVM classification, it was found that using the SAGA algorithm “Supervised Classification for Grids” via the SAGA toolbox in QGIS worked without problems at this point. It was precisely for this reason that it became evident that a combination of the OTB and SAGA plugins in QGIS could lead to very promising results (see conclusion in Chapter 4).

¹⁰ <https://www.orfeo-toolbox.org/CookBook/> [accessed 07.05.2020]

¹¹ For example the segmentation algorithm: https://www.orfeo-toolbox.org/CookBook/Applications/app_Segmentation.html [accessed 07.05.2020]

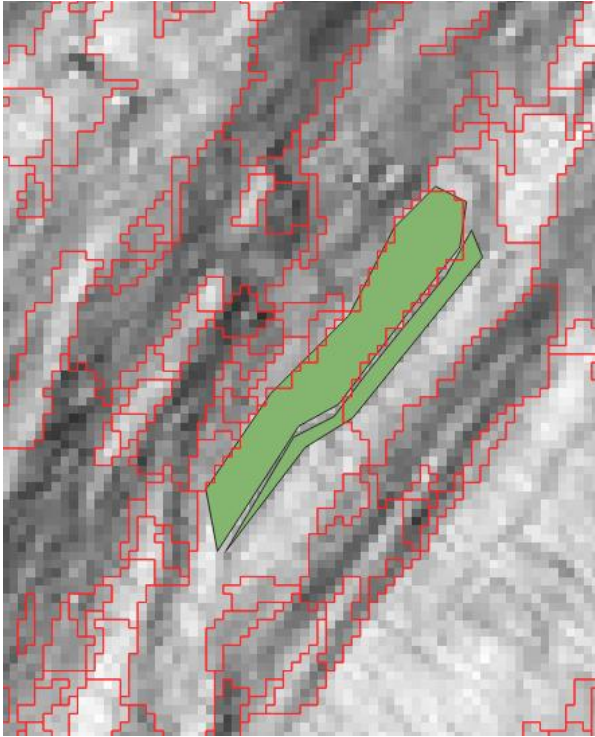


Figure xx: Screenshot of training polygons (green) that intersect multiple segments, leading to inaccurate classifications.

OTB was more difficult to work with than SAGA because the documentation is written in a very technical way that a first time user may find difficult to understand. For instance the author was faced with a recurring error that led to the segmentation algorithm crashing and finding a solution took a while. With every attempt to segment a LiDAR visualisation without a pre-processing step, the algorithm returned an error message regarding the image projection reference, despite the fact that the projections of the project and the visualisation always matched each other. The posting of a query in the very active user-forum resulted in one reply but no solution. However, as soon as the visualisation was cropped or filtered, the segmentation algorithm worked without problems. Two possible reasons for this came to mind: either the original visualisation is protected by copyright in some way, or the image was too large to be handled by OTB. Using too large an image proved to be problematic anyway because it causes the processes to crash or to take significantly too much time to process, so the error was easily avoided by cropping the visualisations to the desired study area as the very first step. Another particularity of OrfeoToolbox is that it cannot handle temporary files, so each output or input needs to be saved.

4.3.3. GRASS GIS

Geographic Resources Analysis Support System (GRASS) GIS (GRASS Development Team, 2018) is a FOSS GIS that can be used for geospatial data management and analysis, image processing, graphics and map production, spatial modelling and visualisation.¹² It was originally developed by the U.S. Army Construction Engineering Research Laboratories as a tool for land management and environmental planning.¹³

GRASS GIS offers a supervised classification tool for manually selecting training classes (figure xxi). Within this tool, the user first defines the classes and then manually adds training polygons to the respective class. These classes are then fed to a maximum likelihood classifier that determines which class each pixel is most likely to belong to. Unfortunately, GRASS requires a minimum of two bands for this task and again, the LiDAR visualisation comes as a single band. As already discussed in the SCP subsection (chapter 4.3.2.1), duplicating the band would be a viable workaround but means that this software is less user friendly than others due to the requirement of an additional step.

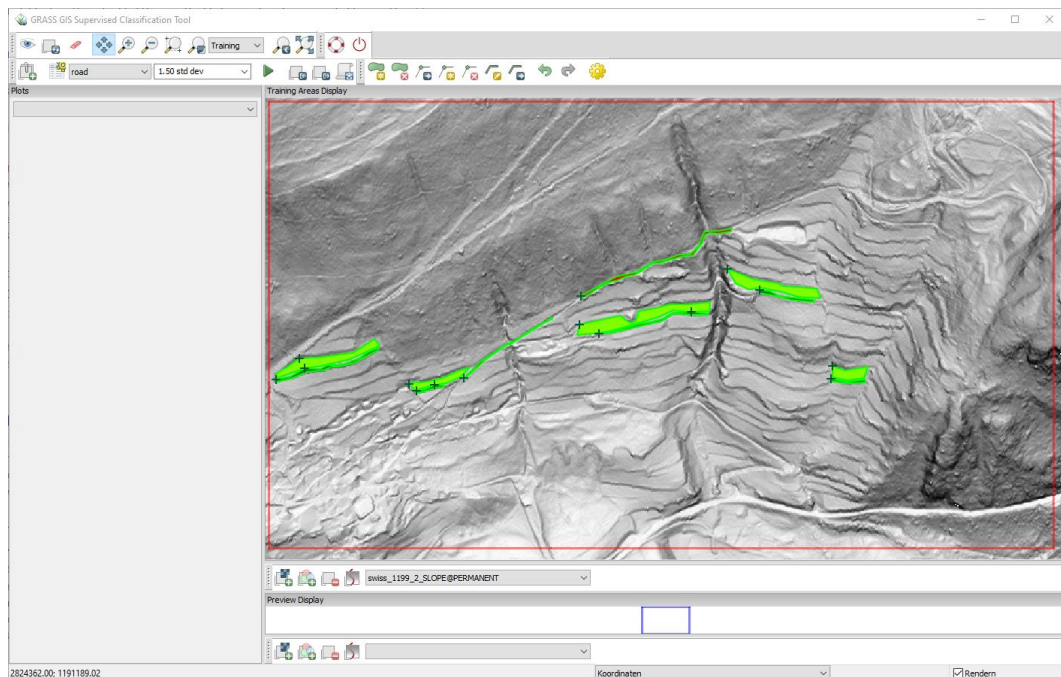


Figure xxi: A screenshot of the supervised classification tool in GRASS GIS after manually adding training polygons.

¹² <https://grass.osgeo.org/> [accessed 12.06.2020]

¹³ <https://grass.osgeo.org/documentation/general-overview/> [accessed 12.06.2020]

There is also a region growing as well as a Meanshift segmentation tool. The output segments come in raster format and are difficult to convert to vectors, thus making the selection of training segments a rather complicated task. It has to be noted that within the documentation of the segmentation algorithm, the authors state that in future, shape will be implemented as a segmentation condition (Momsen *et al.* 2020). This would be a very helpful addition as image objects often possess a specific shape characteristic that could help with the accuracy of the segmentation.

GRASS GIS is a straightforward software to use as the GUI is set up like any other GIS. There is extensive training material available both from GRASS GIS¹⁴ and from private users (eg. Youtube tutorials such as “Supervised Classification in GRASS GIS 7.6.1”¹⁵). There is also a very detailed documentation of all the functionalities available in the online manual (GRASS Development Team, 2018).

4.3.4. Other software

Other GeOBIA capable software listed by Hossain and Chen (2019) is being summarized here because they either didn’t match the criteria of FOSS or user friendliness that were defined in the research aims of this thesis (chapter 1.2), or simply because they were unfindable.

EDISON was unfindable. A Google search did not return any results and the link¹⁶ provided in Hossain and Chen (2019) led to a page that stated “You don’t have permission to access this resource” (Hossain and Chen 2019, 124). GeoSegment requires a prior registration¹⁷ before the software can be used, but the link for registration led to a site that was unavailable.¹⁸

Size-Constrained Region Merging (SCRM) is a stand-alone image segmentation tool that was initially developed by Castilla in 2003 (Castilla *et al.* 2008, 410). This application creates ESRI shapefiles as segmentation outputs and thus, the idea emerged that perhaps SCRM could be used for the initial segmentation step of the workflow before importing the shapefiles into QGIS for the classification step. SCRM can be run within the commercial remote sensing software ENVI (in which case the full workflow would not meet all FOSS requirements) or as a stand-alone

¹⁴ <https://grass.osgeo.org/documentation/tutorials/> [accessed 29.06.2020]

¹⁵ <https://www.youtube.com/watch?v=k7OQ5BLT8Wo> [accessed 29.06.2020]

¹⁶ <http://coewww.rutgers.edu/riul/research/code/EDISON/doc/help.html> [accessed 07.05.2020]

¹⁷ <http://130.15.95.215/lagisa/> [accessed 29.06.2020]

¹⁸ http://localhost/lagisa/lagisa_gui/register_view [accessed 09.06.2020]

application in conjunction with the IDL Virtual Machine (Castilla *et al.* 2008, 413). The IDL Virtual Machine is a free part of IDL and the full version must be downloaded in order to access the Virtual Machine.¹⁹ Even though the use of SCRM in the IDL Virtual Machine is free, the source code of the software is proprietary to the author G. Castilla (Castilla *et al.* 2008, 413). This means that SCRM does not fulfil the FOSS requirements defined in this thesis. Perhaps if one was to contact the author with an interesting project proposal, he would give permission to view the source code, but on the other hand, this goes against the condition set by this thesis that the workflow should be uncomplicated and user friendly. All factors combined, SCRM was deemed unsuitable for the final workflow that will be presented in chapter 5.

The Remote Sensing and GIS Software Library (RSGISLib) is an open source library containing tools for remote sensing and GIS dataset processing (Bunting *et al.* 2014, 225). These tools can be accessed through an xml or Python script, or as a Python function (Bunting *et al.* 2014, 17). Surely, this library is useful to someone with programming skills, but the aim of this thesis was to develop a workflow that didn't require the knowledge of a programming language and thus, the RSGISLib is not a suitable option in this context.

Lastly, SPRING, a stand-alone software for GIS and remote sensing image processing system with an object-oriented approach (Câmara *et al.* 1996) seemed very promising, but unfortunately the image projection reference of the study area (EPSG:2056 – CH1903+ /LV95) is not supported and thus this software was unusable for the purposes of this thesis.

4.4. Discussion and Conclusion

Unfortunately, a number of FOSS GeOBIA solutions did not make it into the testing round. Some like EDISON were simply unfindable, others like SCRM were only seemingly FOSS because although they are free to use, their source-code is proprietary. Some, like the RSGISLib, are simply not user friendly for the general public due to the required programming skills, and others still, like SPRING, cannot cope with all image projection references.

¹⁹ <https://www.harrisgeospatial.com/Support/Self-Help-Tools/Help-Articles/Help-Articles-Detail/ArtMID/10220/ArticleID/17309/The-IDL-Virtual-Machine> [accessed 07.05.2020]

These kinds of problems, of course, do not have to be dealt with when opting for a proprietary software solution, since these offer the benefit of extensive training material for the user and long term support. Trimble eCognition was clearly developed for (semi-)automatic image analysis as the algorithm library hosts a number of very handy tools. Additionally, eCognition allows for communication between object classes and unleashes the full potential of the neighbourhood and hierarchical relationships that Sevara and Pregesbauer discuss (Sevara and Pregesbauer 2014, 141). For more information on these relationships please consult chapter 3.2.3. eCognition is much less intuitive to use than ERDAS IMAGINE because it does not resemble any other software (at least none known to the author). ERDAS IMAGINE offers a very intuitive userface that strongly resembles that of AutoCAD. Additionally, perhaps because of the simplicity of the region growing and classification algorithms, it is very easy to use and understand. Nonetheless, the benefits of software such as eCognition and ERDAS IMAGINE are dampened by the fact that their source codes are not accessible and thus the workflows and rulesets developed within them are never truly reproducible. The loss of reproducibility is the main reason why the future of image analysis workflows should be FOSS.

Of all the tested FOSS solutions that did meet the set criteria of this thesis, SAGA was the most intuitive and easy to learn. In addition to this, good results can be obtained with minimal time and effort, using just two algorithms and the selection of training segments. OTB also led to good results but with much more time and effort. On the plus side, OTB offers a range of additional preprocessing and processing tools that SAGA does not offer. Despite the additional tools offered by Orfeo Toolbox, the user friendliness of SAGA cannot be trumped. The semi-automatic classification plugin was very intuitive and the developer offered detailed training material, however, single band images are not supported and while there is a workaround (chapter 4.3.2.1), this additional step makes this tool less user friendly than others. GRASS GIS, while being a very intuitive, well documented software, had the same issue. Unfortunately, there are no FOSS applications that offer the consideration of neighbourhood relationships as is the case for Trimble eCognition. Perhaps this will be implemented in a future version of one of the FOSS applications.

The following table (table iii) summarises the benefits and drawbacks of each of the programmes that made it into the testing round.

Table iii: Benefits and drawbacks of the tested software.		
Software	Benefits	Drawbacks
eCognition	Powerful tools that incorporate hierarchies/ neighbourhood relationships	Takes time to get to grips with, proprietary
ERDAS IMAGINE	Very intuitive GUI	Proprietary
System for Automated Geoscientific Analyses (SAGA) GIS	Easy to work with, good training material	Less pre-processing options than others
Orfeo Toolbox (OTB)	Extensive toolbox, many options	Cannot handle temporary files, more difficult to get to grips with than others
Semi-automatic classification plugin (SCP)	Very intuitive, good training material	Single band LiDAR visualisations unsuitable
Geographic Resources Analysis Support System (GRASS) GIS	Very good documentation, intuitive to work with	Single band LiDAR visualisations unsuitable

The second research question asked: Is there an open source solution for GeOBIA available with a Graphical User Interface (GUI) that is user friendly, does not require additional coding and will prove through systematic testing to be capable of classifying the heterogeneous and linear features within the terraced landscape of the Lower Engadine? To this question, the answer would have to be yes, SAGA GIS is open source, intuitive and very user friendly in the sense that it does exactly what is necessary for a GeOBIA workflow, not more and not less. OTB is also a very powerful tool that offers a wider variety of tools, but these additional options makes it a more complicated tool to get to grips with and to use.

For the custom workflow however, it was decided to combine SAGA and OTB in QGIS precisely because both software offer different benefits. This solution also has the added benefit of having the possibility to implement as much of the developed workflow into the graphical workflow modeller of QGIS. The resulting workflow will be discussed in the following subsection.

5. Developing a custom GeOBIA workflow

The second aim of this thesis was to create a custom GeOBIA workflow for the heterogeneous landscape of the Lower Engadine. The two main requirements for this workflow are 1) that only open source software solutions should be used as this promotes accessibility, transparency and reproducibility of the research and 2) it should be easy to use for archaeologists who do not have a background in programming. To summarise these aims in a research question: What are the elements that an effective FOSS GeOBIA workflow for heterogeneous and linear archaeological objects needs to contain?

As mentioned in chapter 4.4, testing the different FOSS GeOBIA software led to the idea of designing the workflow in QGIS due to the possibility of combining the SAGA plugin with the OTB plugin. Designing the workflow in QGIS had the added benefit that many users already know how to use the programme and thus the workflow would be very intuitive. Another reason for choosing to work in the QGIS environment was the graphical workflow modeller that would allow further simplification of the workflow for the user. For a complete overview of the QGIS layer structure that was generated for this thesis, please consult appendix i.

In chapter 2.3.3, the two main terrace types were introduced. It was decided that the final workflow should include a step that shows possible candidates of both terrace types. This chapter will present the tests that were carried out in order to evaluate the different options and steps that led to the final workflow. Subsequently the final workflow will be presented.

5.1. Testing phase

As mentioned in chapter 4.3.2.2, the Orfeo Toolbox offers a Large Scale Meanshift Classification workflow in QGIS but this workflow has some disadvantages. The main disadvantage is that the training areas need to be entered as polygon shapefiles, and merging the attribute tables of these training shapefiles and the segments leads to errors such as segments being intersected by multiple training polygons. It seems that the most elegant solution for GeOBIA is the one presented by SAGA: segmenting the image and adding a training data column in the attribute table in order to have the necessary statistics for the subsequent supervised image classification.

During the testing phase, different LiDAR visualisations, smoothing filters, segmentation algorithms and training data options were tried out, the results of which will be presented in the following subsections.

5.1.1. LiDAR visualisations

Because the GeOBIA workflow in SAGA proved to be so easy to work with, it was decided to classify a sample image of the lower, clearly defined terraces as well as a sample image of the upper, less clearly defined terraces in order to assess which visualisation works best for each area.

The Digital Terrain Model (DTM) was used to create nine different LiDAR visualisations using the Relief Visualisation Toolbox (RVT) version 2.2.1 (Kokalj and Somrak 2019; Zakšek *et al.* 2011). These visualisations were analytical hillshade, hillshade from multiple directions, simple local relief model, sky view factor, local dominance, slope, and finally, positive and negative openness. For an explanation of these visualisations, please consult table iv. The parameters that were used to generate these visualisations were obtained from the recommendations for steep and complex terrain provided in the manual “Airborne laser scanning raster data visualization: A Guide to Good Practice” (Kokalj and Hesse 2017).

Table iv: Summary of the different LiDAR visualisations that were generated and used for testing purposes (after Kokalj and Hesse 2017).	
Name	Description
Analytical hillshade	Representation of how the relief surface reflects incoming illumination, in this case from the upper left corner.
Analytical hillshade from multiple directions	In this case, the relief is illuminated from multiple directions, the result is a multiband image.
Skyview factor	Representation of the portion of sky visible from each pixel.
Positive openness	Representation of the mean zenith angles of all determined horizons within a given search parameter (Not just of the sky as in skyview factor)
Negative openness	Representation of the mean nadir angles of all determined horizons within a given search parameter (Not just of the sky as in skyview factor)

Simple local relief model	Removal of large scale morphological elements, thus representation of local, small scale elevation differences.
Slope	Representation of the maximum rate of change between the elevation of each cell and its neighbours.
Local dominance	Computation of how dominant an observer standing over each point would be for the local surrounding area.

The choice of visualisation methods was based on the work of Nyffeler (2018), who provides an overview of the benefits and drawbacks of each method (Nyffeler 2018, 44), except that in this thesis no principal component analysis (PCA) of the hillshade from multiple directions was carried out and a simple local relief instead of a regular local relief was generated. However, the benefits and drawbacks compiled by Nyffeler (2018) still apply as the PCA is a summary of the data generated for the hillshade from multiple directions and the simple local relief visualisation is merely a simplified process for generating a relief visualisation (Kokalj *et al.* 2019, 5). The benefits and drawbacks listed by Nyffeler (2018) were translated and can be found in the following table (table v).

Table v: Benefits and drawbacks of the Visualisations used by Nyffeler (Nyffeler 2018, 44). Original in German: translated by Pierina Roffler.		
Visualisationmethod	Benefits	Drawbacks
Hillshade	<ul style="list-style-type: none"> • Can be generated as dynamic function in GIS • Easily readable • Good overview of the topography 	<ul style="list-style-type: none"> • Structures parallel to the lightsource are not visible • Over- and underexposure in areas with pronounced relief • Artificial relief inversion if lighting comes from the south
Principal Component Analysis ²⁰	<ul style="list-style-type: none"> • Shows reliefs in great detail • Good overview of the topography 	<ul style="list-style-type: none"> • Uses a lot of storage space • Readability is hindered by colouration • Possible relief inversion if topography is very pronounced
Slope	<ul style="list-style-type: none"> • Can be generated as dynamic function in GIS • Easily readable 	<ul style="list-style-type: none"> • Not suitable for even terrain

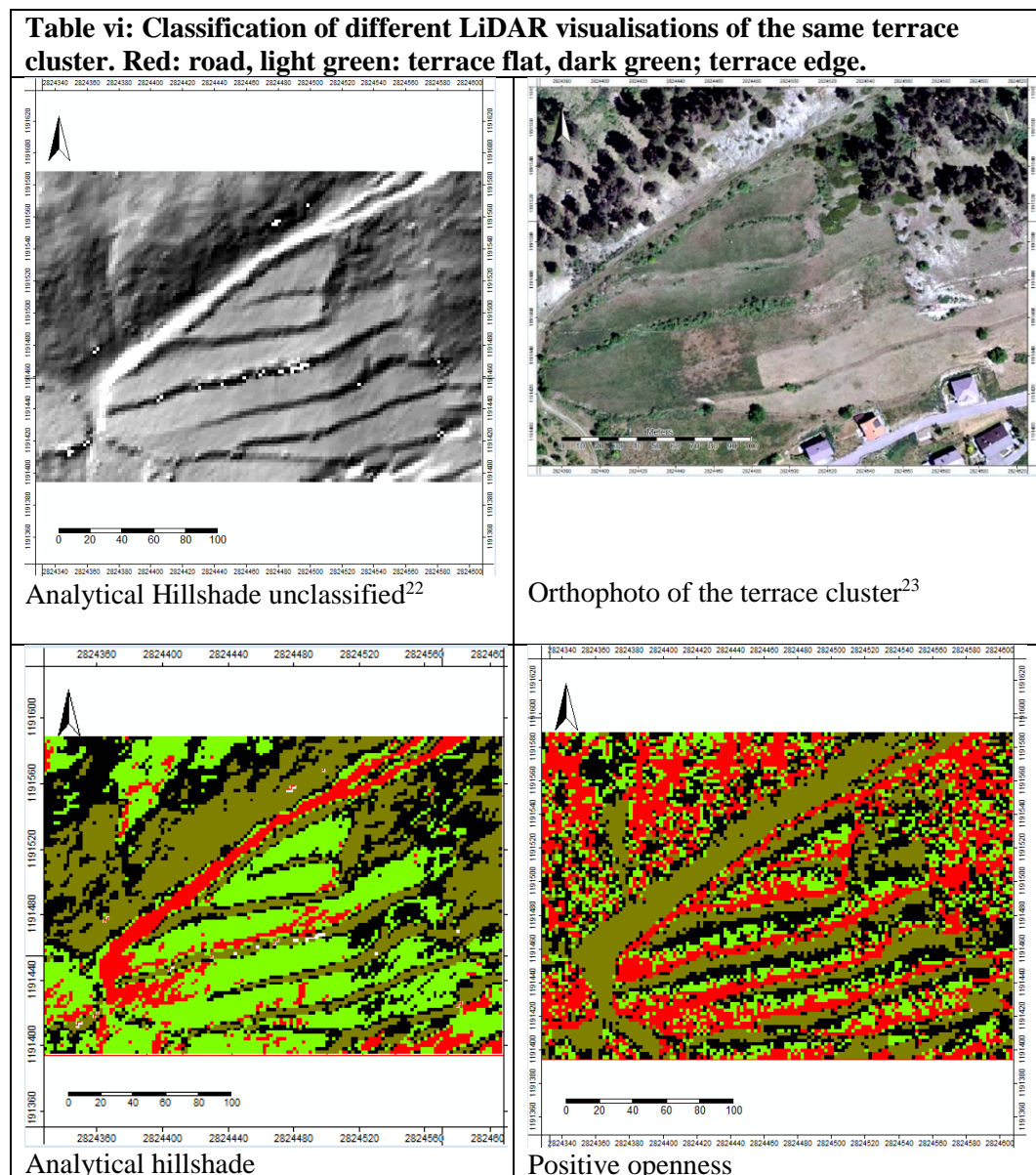
²⁰ In this thesis: "Hillshade from Multiple Directions".

	<ul style="list-style-type: none"> • Suitable for distinct structures in hillside situations 	
Positive Openness	<ul style="list-style-type: none"> • Consistent display of small-scale structures independent of their position within the relief • Good addition to SVF 	<ul style="list-style-type: none"> • Missing of general topography impedes interpretation • Insufficient display of faint structures
Negative Openness	<ul style="list-style-type: none"> • Consistent display of small-scale structures independent of their position within the relief • Precise mapping of negative, linear structures 	<ul style="list-style-type: none"> • Missing of general topography impedes interpretation
Sky View Factor	<ul style="list-style-type: none"> • Easily readable • General topography is visible • Visualisation of faint structures in hillside situation • Visualisation of negative structures 	<ul style="list-style-type: none"> • Insufficient display of faint structures in even terrain • Visibility of small-scale structures is dependent on their position within the relief
Local Dominance	<ul style="list-style-type: none"> • Visualisation of very faint structures • Only weak noise 	<ul style="list-style-type: none"> • Unclear structure borders impede precise mapping • Abstract visualisation impedes interpretation • Generation is time intensive
Local Relief Model ²¹	<ul style="list-style-type: none"> • Visualisation of very faint structures 	<ul style="list-style-type: none"> • Abstract visualisation impedes interpretation • Not suitable for terrain with a pronounced relief • Generation is time intensive

Because the “supervised classification for grids” algorithm in the SAGA toolbox in QGIS does not support multiband images, the analytical hillshades from multiple directions were unsuitable for the final workflow. It was clear from the benefits and drawbacks listed by Nyffeler (2018) that some visualisations such as Sky View Factor and Slope were going to be more suitable for the study area than others, but it was nonetheless decided to test them all.

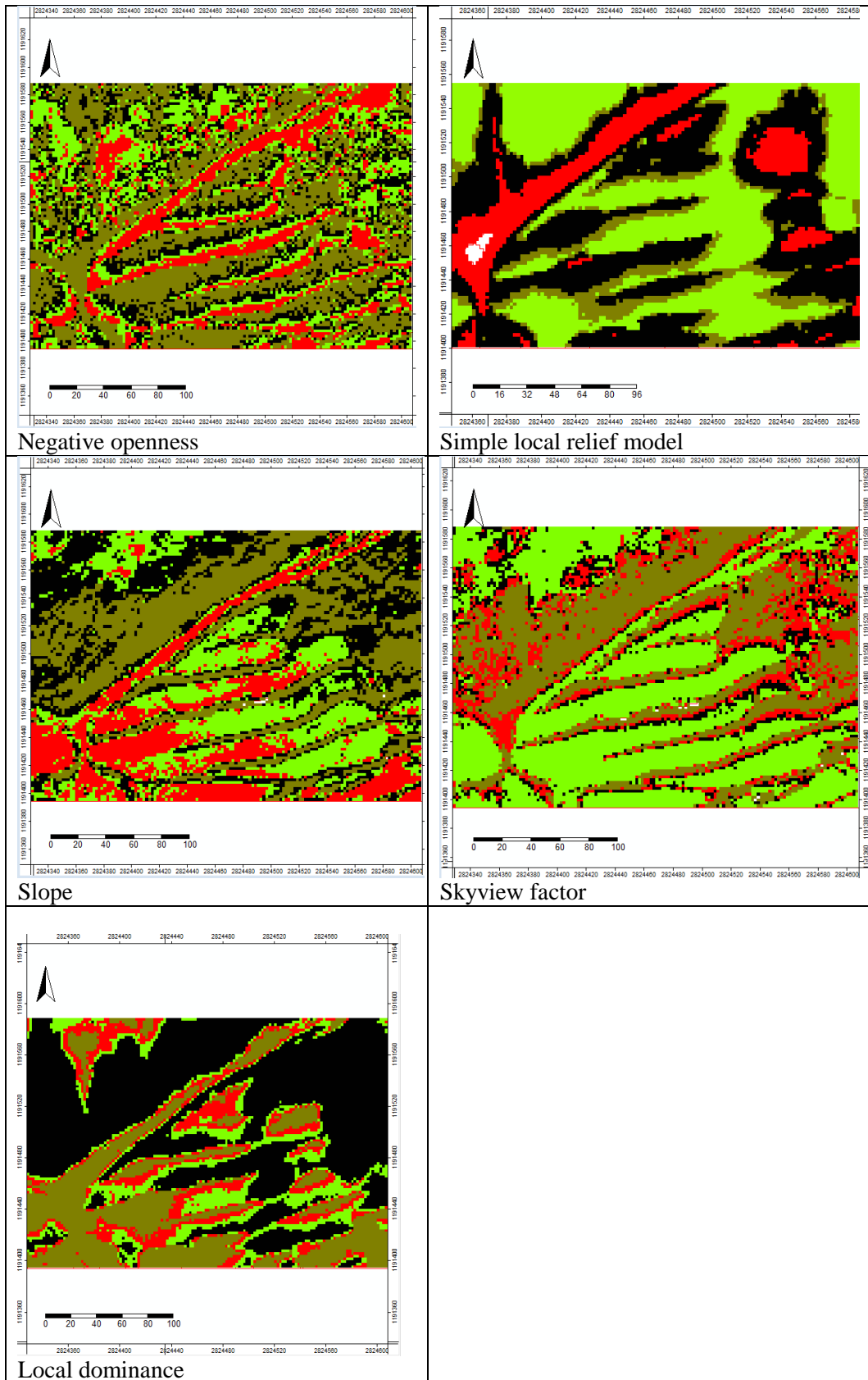
²¹ In this thesis: “Simple Local Relief Model”.

After their generation, the visualisations were segmented, training data added to the segment attribute tables and subsequently classified according to the workflow presented in chapter 4.3.1. The final classification for the lower study area featured a sample terrace cluster that contained three object classes: terrace flat (light green), terrace slope (dark green) and a road (red). This cluster was chosen because it is geographically separated from other terraces and thus all terraces could be classified completely without cutting others off at the edge of the clipping (figure xxii). The results are summarised in table vi.



²² DTM: Bundesamt für Landestopografie, 2019; visualisation created in RVT2.2.1 (Kokalj and Somrak 2019) by Pierina Roffler.

²³ Bundesamt für Landestopografie, 2019.



The process was repeated for the upper study area where the objects are much more diffuse. In addition to the regular visualisations, a nonlinear smoothing filter was

applied to noisy visualisations in order to assess whether smoothing would improve the classification. Different smoothing filters will be discussed in more detail in chapter 5.1.4. For testing purposes, a part of the upper study area was chosen that the author was familiar with as it was one of the focus areas of the TERRA project (figure xxii).

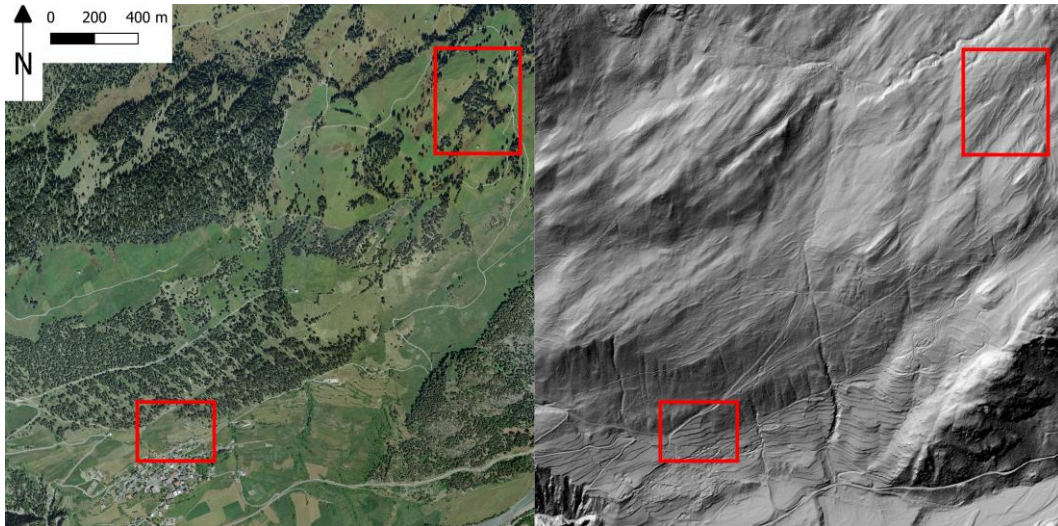


Figure xxii: Location of the lower testing terrace cluster (bottom left) and the upper testing area (above right) within an orthophoto (left) and a hillshade visualisation of the DTM (right) (Bundesamt für Landestopografie, 2019).

It was soon realised that if anything other than terrace flats and terrace slopes is classified, the classification of the terrace object classes is less distinct. This is due to the fact that these objects are very similar in their appearance, not only in the field but also in the DTM and the visualisation, meaning that their values are also largely the same (Chapter 5.1.2). Because of this similarity in values, the selection of training data from these segments leads to a more diffuse classification result (figure xxiii)²⁴.

²⁴ QGIS Layers “regular watershed classification” and “regular watershed classification no roads”.

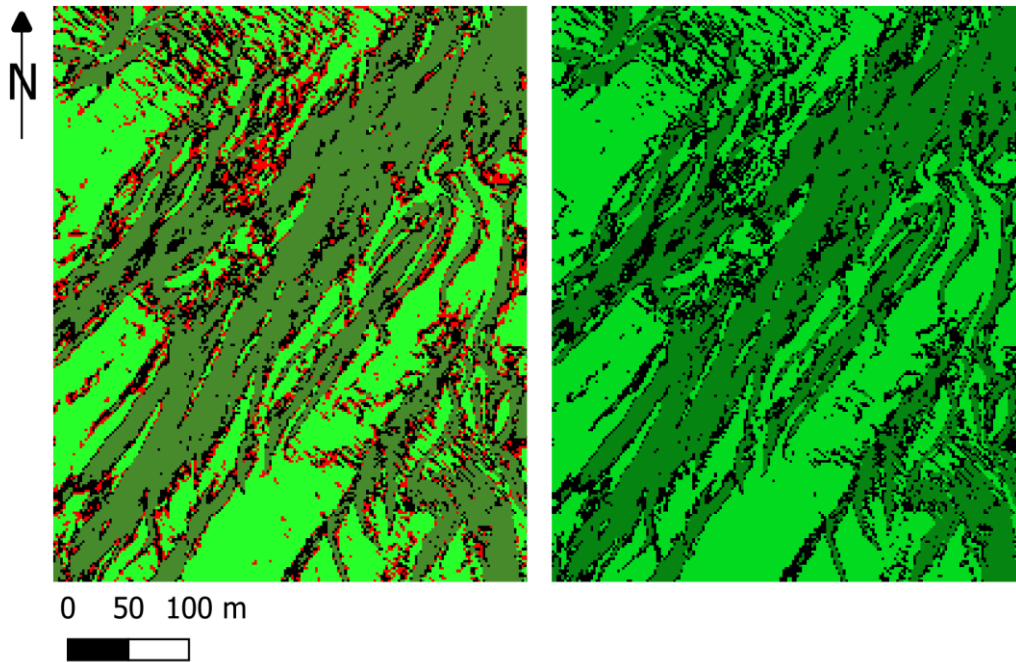
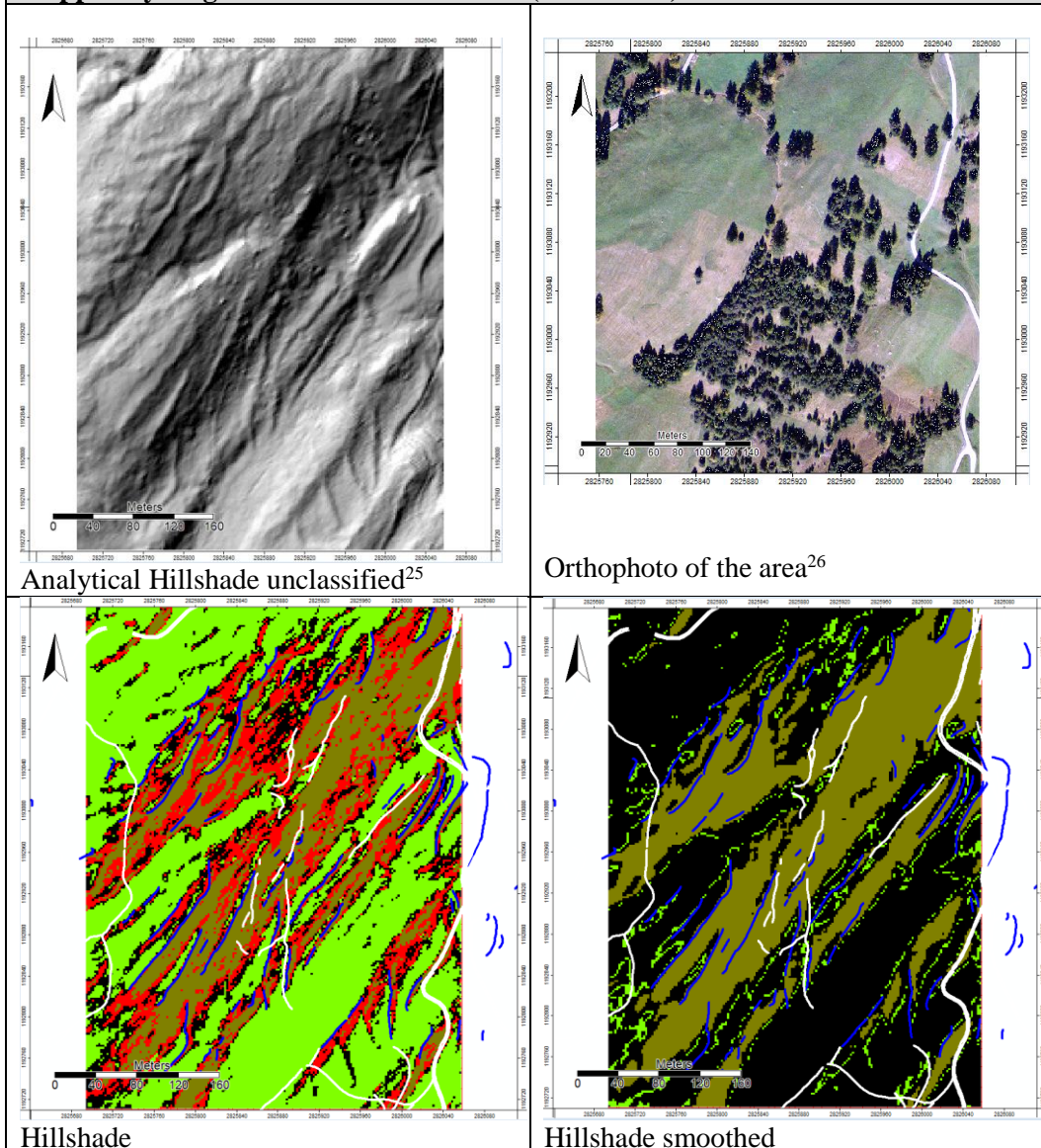


Figure xxiii: Classification with roads (left) leads to a more diffuse result than if only terrace flats and edges are classified (right). Roads: red, terrace flats: light green, terrace slopes: dark green.

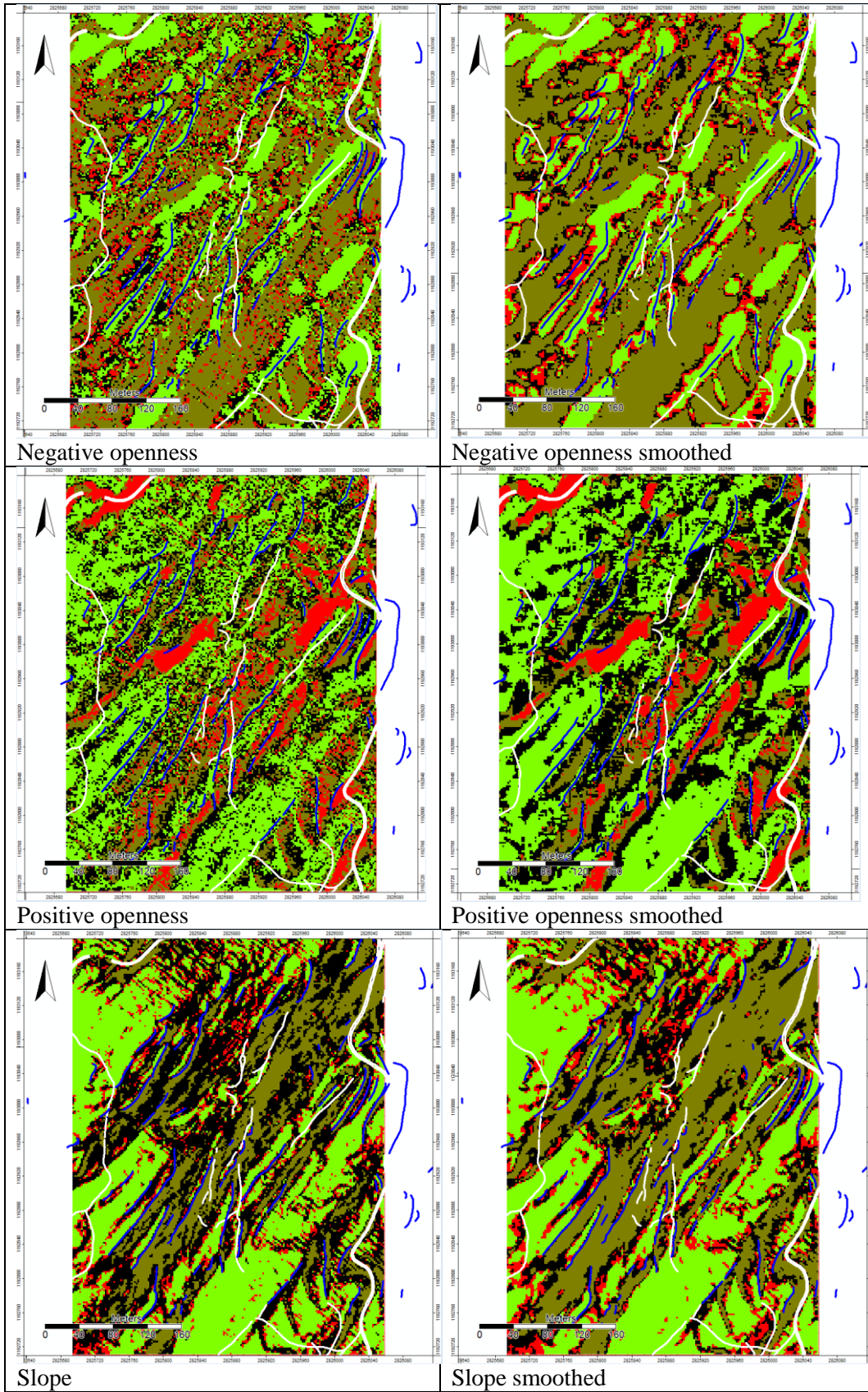
The choice of objects for classification will be discussed in more detail in chapter 5.1.2. In table vii, the results from the upper study area are summarised. Again, terrace flats are shown in light green, terrace slopes in dark green and the road class in red. For better orientation, terrace edges are shown in blue and roads are shown in white. These overlaid white and blue mapping results were kindly provided by Angelika Abderhalden-Raba, and these data will be discussed in more detail in chapter 5.4. Here, it is very clear that the classification of roads made little sense and only led to a more diffuse classification result for the terrace object classes.

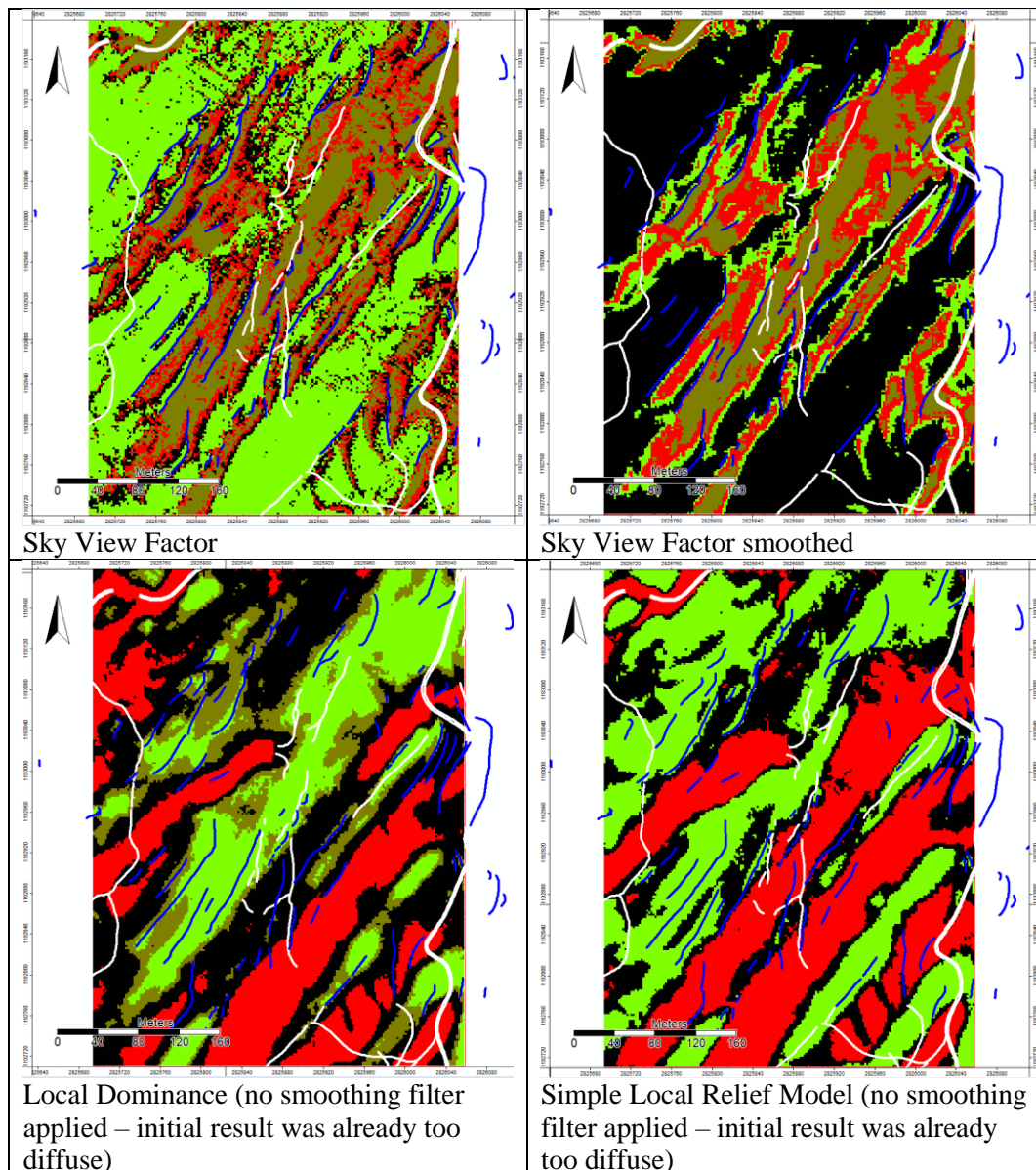
Table vii: Classification of different LiDAR visualisations of terraces and roads in the upper study area. Red: road, light green: terrace flat, dark green; terrace edge. Overlaid in blue are the terrace edges and in white the roads that were mapped by Angelika Abderhalden-Raba (Raba 1996).



²⁵ DTM: Bundesamt für Landestopografie, 2019; visualisation created in RVT2.2.1 (Kokalj and Somrak 2019) by Pierina Roffler.

²⁶ Bundesamt für Landestopografie, 2019.





While hillshades clearly work quite well for the lower study area, this was not the case in the upper study area where the clearest result was achieved with the slope visualisation. The issue with the hillshade visualisation is that structures which are parallel to the lighting do not show up and depending on the terrain, the lighting may not be optimal for all areas in the image (Nyffeler 2018, 44). The terraces in the lower study area are all more or less oriented in the same direction and are located on the side of a steep hill while those in the upper study area are much more irregular and located in less steep terrain. The slope visualisation is not dependant on lighting and topography, which is why it generates a very consistent visualisation for all parts of the study area, regardless of the general terrain morphology. Local Relief Models are unsuitable for terrain with strong relief and the borders of objects

in the Local Dominance visualisation are unclear (Nyffeler 2018, 44), making the selection of training segments a very difficult task. For this reason, these visualisations are entirely unsuited for this particular study area, and the test results in table vii confirm this. Positive Openness does not display faint structures sufficiently and Negative Openness is mostly suitable for displaying negative structures (Nyffeler 2018, 44) so these two visualisations are also unsuitable for the study area. Sky View Factor was deemed promising as it was described as being suitable for visualising faint structures in hillside situations (Nyffeler 2018, 44), but the test results clearly indicate that the terraces and roads are less accurately classified than with a hillshade or slope visualisation (table vii).

In order to achieve the most consistent results possible, it was decided to work henceforth with slope visualisations for both the upper and the lower study area. This choice also further simplifies the workflow because, in a later step, the slope visualisation is needed in order to identify the candidates for the two different terrace types (chapter 5.1.5).

The smoothing filter led to more aesthetically pleasing results but upon closer consideration, it became apparent that the unfiltered version, while being slightly less aesthetic, delivers the more honest result. Despite this, it was decided to test other smoothing filters in QGIS, and the results of these tests will be discussed in chapter 5.1.4.

5.1.2. Objects requiring classification

In the previous chapter it was already indicated that some objects were difficult to be classified. The main problem is that even in the field, roads, paths and irrigation or drainage/irrigation systems are difficult, and sometimes even impossible, to tell apart (for an example see chapter 2.3.3, figure vii). This is obviously no different in the LiDAR visualisation (figure xxiv).²⁷

²⁷ QGIS Layers “slope cropped”, “ra85drainage” and “ra85paths_roads”.

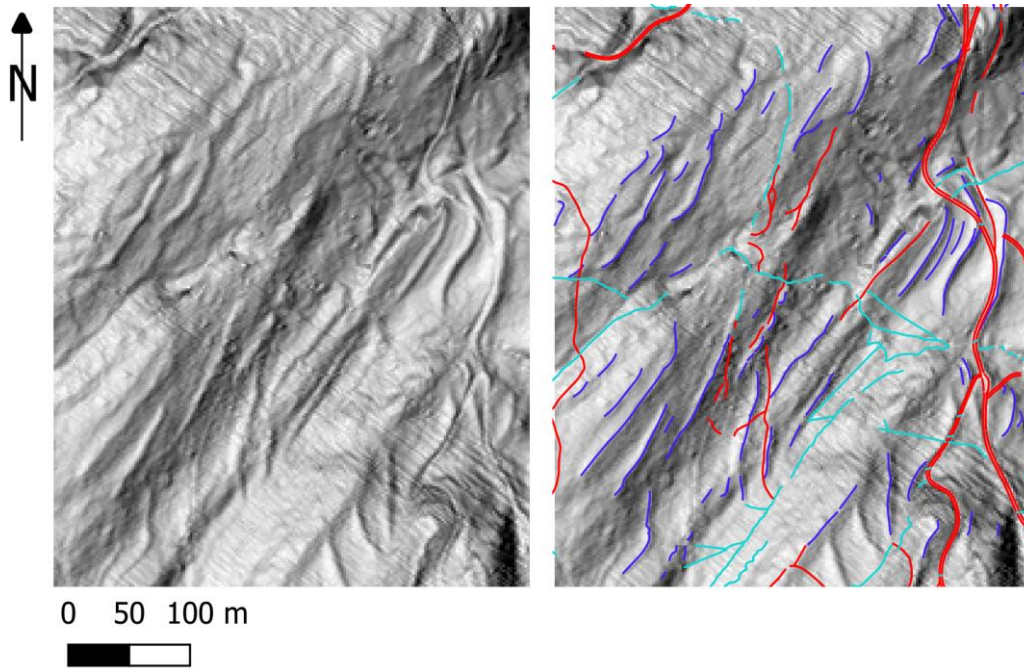


Figure xxiv: Slope visualisations containing terraces, drainage/irrigation ditches and roads. As a reference, the image on the right shows the mapping results of Raba (1996) with the terrace edges in dark blue, the drainages in light blue and the roads shown in red (DTM: Bundesamt für Landestopografie (2019), visualisation created in RVT2.2.1 (Kokalj and Somrak 2019) by Pierina Roffler).

Because these objects are so similar in their appearance, their values in the DTM and the visualisation are also largely the same. This means that the selection of training data from these segments leads to a very diffuse classification, if any at all. Because the visualisation tests in SAGA (Chapter 5.1.1) showed that the classification of terrace flats and slopes is less accurate if training data from roads are inserted, it was decided to leave the classification of these objects aside and focus instead only on the identification of terrace edges by classifying the terrace flats and slopes as accurately as possible.

5.1.3. Training data

As was already mentioned in chapter 4.3.2.2, the manual creation of Region Of Interest (ROI) polygons, followed by merging these with the segment attributes is a rather inaccurate method. If a ROI polygon intersects several segments, this can lead to one segment being assigned two training classes or, depending on the merging method of choice, the wrong training attributes.

Another method is to create an xml file for the class statistics. This method works for the OTB Large Scale Meanshift workflow, because during this workflow, not only the segment-ID but also the mean and variance statistics of each band are calculated in the attribute table. This method is important for multiband images as

the class statistics take into consideration the mean and variance values of each band. However, because LiDAR visualisations contain only one band, this step does not refine the training classes any further than the more straightforward manual training input via attribute table. Additionally, leaving out the generation of the XML statistics file means one processing step less, again promoting user friendliness for those who are only just getting started with GeOBIA.

For the above mentioned reasons, it was decided to manually edit the attribute table of the segmentation layer in order to add a field for training data, followed by the manual selection of meaningful segments as training data for each of the two object classes.

5.1.4. Smoothing filters and segmentation algorithms

Between the SAGA and OTB toolboxes, there were six different smoothing filters available for consideration: SAGA offers the options exponential, nonlinear, and Gaussian while OTB provides Mean, Large Scale Means Shift (LSMS), Gaussian and Anisotropic Diffusion (Anidif) smoothing filters.

The author found no information on the type of exponential and nonlinear filters that are offered by SAGA. OTB on the other hand offers Anisotropic Diffusion as a specific type of nonlinear filter and Gaussian smoothing is a type of exponential filter. For this reason, it was decided to consider only the smoothing algorithms provided by OTB.

Gaussian and Mean smoothing are filters that blur the images to remove not only noise but also detail (Figure xxv).²⁸ By contrast, LSMS smoothing and Anidif are smoothing algorithms specifically designed to reduce image noise without removing edges, lines or other image details. Because of this quality, these two filters were deemed suitable for the study area in the hopes that the terrace edges would be left largely unchanged but with a general noise reduction in the areas around them.

²⁸ QGIS layers “gaussian smoothing” and “mean smoothing”.

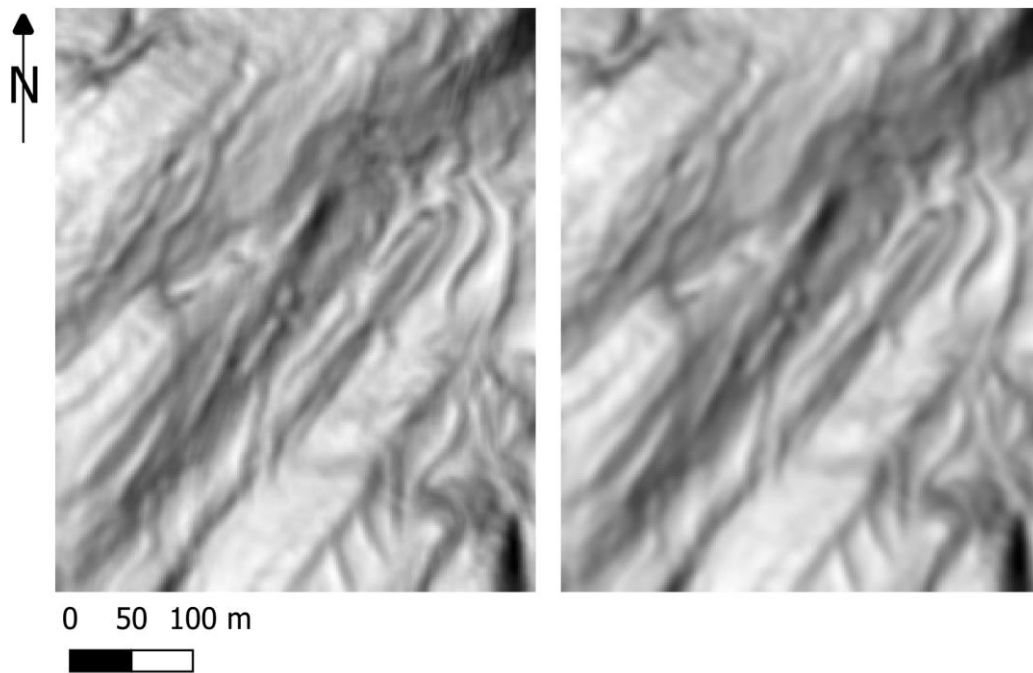


Figure xxv: The results of the Mean (left) and Gaussian (right) smoothing algorithms led to very blurred visualisations (DTM: Bundesamt für Landestopografie (2019), visualisation created in RVT2.2.1 (Kokalj and Somrak 2019) by Pierina Roffler).

For testing purposes, a regular, unfiltered slope visualisation as well as the LSMS and Anidif smoothing filters were applied, followed by segmentation and classification. For testing purposes, all three images were segmented both with a Watershed and a Meanshift segmentation algorithm.

Simply put, Watershed segmentation works by simulating the flooding of the image, recording local maxima and minima as the water pools at the minima. In order to counteract an over segmentation, a depth threshold can be defined which establishes the minimum depth of a pool, thus combining local minima together until this minimum depth is achieved. By experimentation, it was found that for the Watershed segmentation, leaving all parameters to default except for the depth threshold, which was changed to 0.05, led to the best segmentation results (figure xxvi). “Best” in this case means that some of the segments are merged to larger regions without reaching a state of under segmentation. The image is still largely over segmented, but an over segmentation is much easier to deal with than an under segmentation.

Meanshift segmentation is a region growing algorithm that replaces each pixel with the mean of pixels in a predefined neighbourhood range, and this neighbourhood must be within a predefined distance of the pixel. For the Meanshift segmentation,

it was found that leaving all values to default except the range radius, which was changed to 1, and the spatial or distance radius, which was changed to 50, led to the best results (Figure xxvi)²⁹. Again, “best” in this case means the largest segments possible without the image being under segmented. While the Meanshift segmentation may seem like the clearer choice compared to the Watershed segmentation due to the larger size of segments, upon closer consideration it was found that some segments of the Meanshift segmentation results span multiple objects (Figure xxvi). An example of a segment that spans multiple terrace slopes and flats is indicated in yellow. It was thus decided to work with the Watershed segmentation in the final workflow.

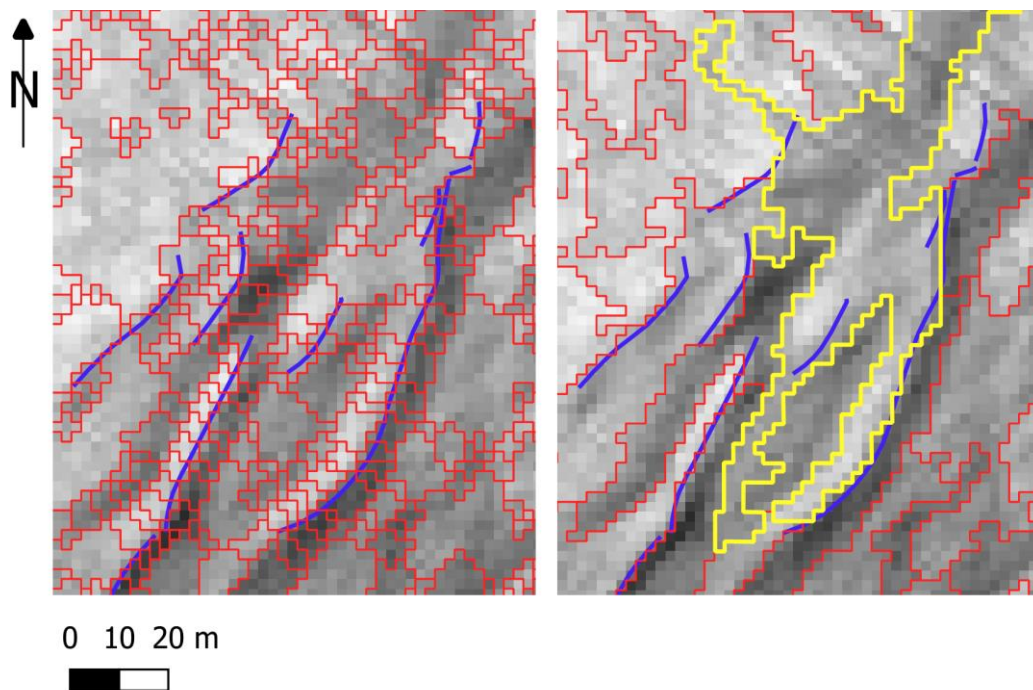


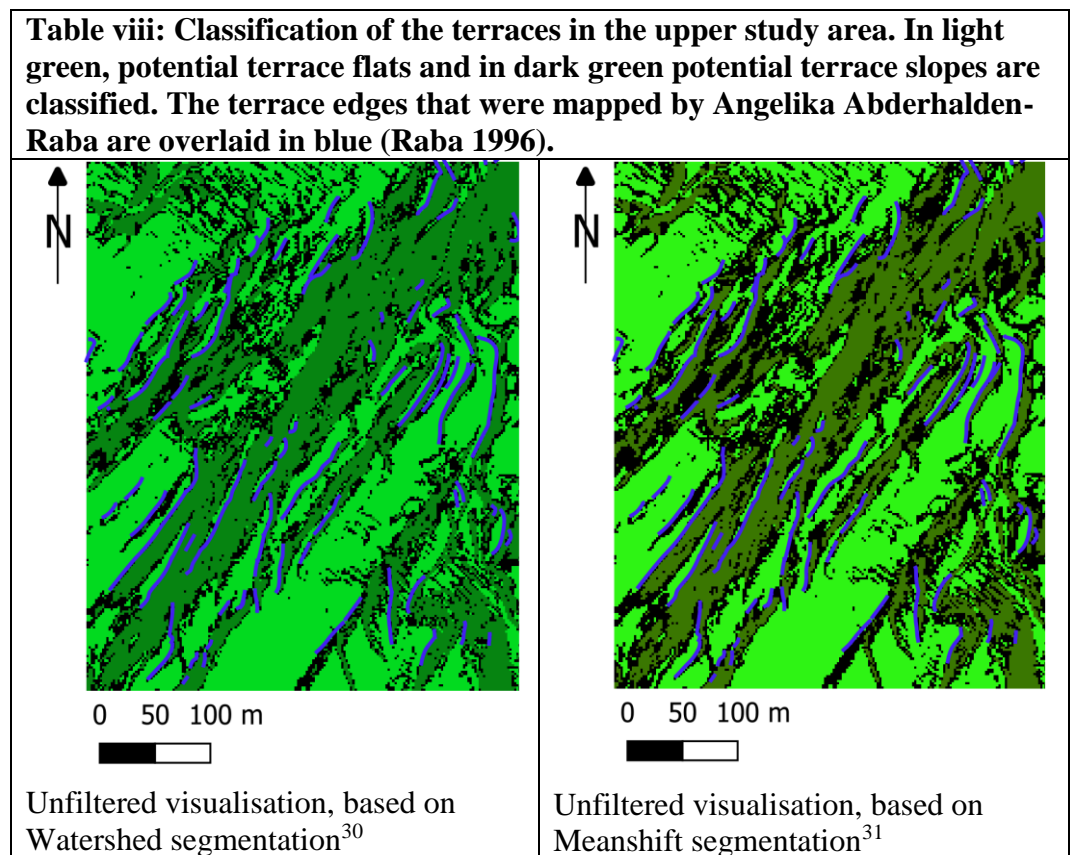
Figure xxvi: The results of the Watershed (left) and Meanshift (right) segmentation. An apparent over segmentation in the Watershed segmentation is needed for exact training segments. One of the meanshift segments that spans multiple terrace flats and slopes is highlighted in yellow (DTM: Bundesamt für Landestopografie (2019), visualisation created in RVT2.2.1 (Kokalj and Somrak 2019) by Pierina Roffler).

For both segmentation options as well as the two smoothed and a regular, unsmoothed slope visualisation, the training and classification procedure was the same. The attribute table of the segmentation layers was opened, the default segment-ID column was deleted and a new column for the training data added. Then, segments that represented the terrace edge and terrace flats were selected and given either class 1 (flat) or class 2 (slope). Next, the SAGA toolbox algorithm

²⁹ QGIS Layers “slope cropped”, “segments regular watershed”, “segments regular meanshift” and “ra85terrace”.

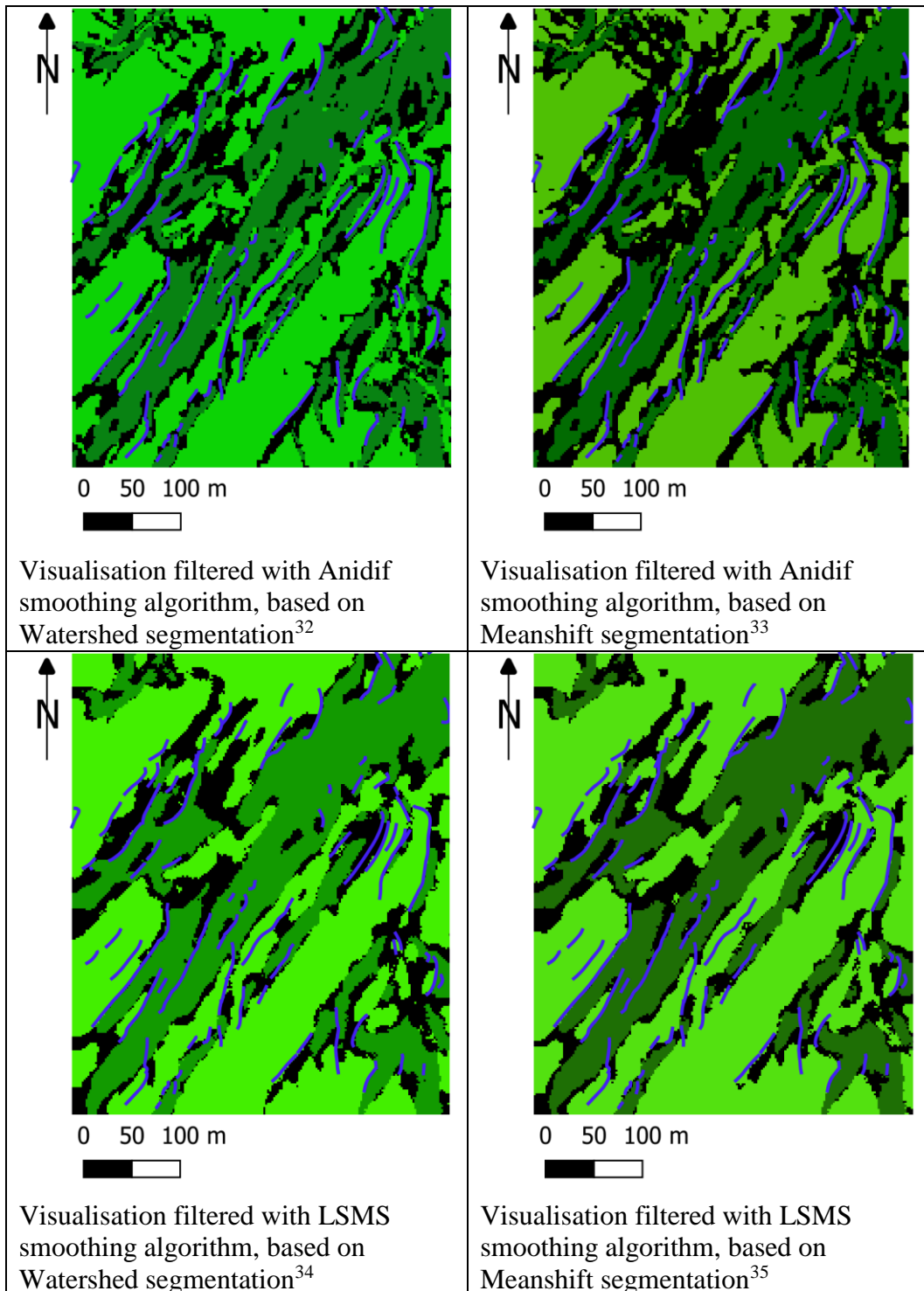
“Semi automatic classification for grids” was used and the segmentation layer was selected as training data. This led to 6 different classifications (table viii).

It was decided based on these six classification results that the unfiltered visualisation along with the Watershed segmentation led to the most accurate results. Smoothing filters lead to more homogeneous, less pixelated results but the author realised that this comes at the cost of a loss in accuracy. For this reason, the final workflow makes use of the Watershed segmentation of an unfiltered visualisation input and uses the attribute table to directly input training classes.



³⁰ QGIS layers “regular watershed classification no roads” and “ra85terrace”.

³¹ QGIS layers “regular meanshift classification” and “ra85terrace”.



5.1.5. Identification of different terrace types

As presented in chapter 2.3.3, there are two terrace types that differ in their morphology; terrace type one has a flat inclination of more than 20% and a slope

³² QGIS layers “anidif watershed classification no roads” and “ra85terrace”.

³³ QGIS layers “anidif meanshift classification no roads” and “ra85terrace”.

³⁴ QGIS layers “lsms watershed classification no roads” and “ra85terrace”.

³⁵ QGIS layers “lsms meanshift classification” and “ra85terrace”.

inclination of 40-100% while terrace type two has a flat inclination of 0-15% and a slope inclination of 20-50%. Type one predominantly appears within the lower study area and type two within the upper study area. Because these two types differ in their morphology, it is also possible to identify them within the classification. For this purpose, the slope visualisation of the entire study area can be filtered to highlight certain inclinations and then layered over the classification. This way, not only areas that are potential terrace flats and slopes can be identified, but if these flats and slopes are also of the terrace type specific inclination, they can be addressed as terraces of said type. For example, if inclinations between 0 and 15% are shown in yellow and inclinations between 20 and 50% are shown in red, then all areas that are displayed in light green and yellow as well as dark green and red are potential terraces of terrace type two. Concrete examples can be found in chapter 5.4.

It is important to note that the slope visualisation generated by the RVT (Kokalj and Somrak 2019; Zakšek *et al.* 2011) contains elevations that are shown in degrees, not in percentages (Kokalj *et al.* 2019, 5). For this reason it is essential to convert the percentages of the terrace flat and slope inclinations summarised in chapter 2.3.3 to degrees. This means that terrace type one has a flat inclination of more than 11.31° and a slope inclination of $21.8-45^\circ$ while terrace type two has a flat inclination of $0-8.53^\circ$ and a slope inclination of $11.31-26.57^\circ$.

5.2. Final workflow

The final workflow comprises of a total of six steps, with an optional seventh step that can be added as needed (figure xxvii).

First of all, the input LiDAR visualisation needs to be cropped to the desired study area. Depending on the size of the study area, it is advisable to split it into smaller areas. This is due to the fact that especially the Watershed segmentation returns a large number of segments and the classification step takes a very long time if all these segments need to be taken into consideration simultaneously. A lot of time is saved by splitting the study area up into manageable tiles, especially because QGIS may even crash after a while during the classification step if too many segments are processed at the same time. It is not possible to define an absolute upper limit for these tile sizes as this depends on the computational power of the computer. The author used a HP Elitebook 820 G3 with an Intel Core i5 CPU and 8GB of RAM

and found a tile size of 500x500 pixels to be the upper limit for the classification step. Cropping is best done with the GDAL algorithm “clip raster by extent”, where a dynamic area can be selected directly on the image that is to be cropped, or by saving the LiDAR visualisation as a VRT (Virtual Raster Tile) dataset and specifying the VRT tile size in the process. Unfortunately, this tiling process results in edge-effects, meaning that around the tile edges, misclassifications can occur due to image objects being cut off. A workaround for this problem is to split the images twice and varying the tile borders slightly in order to ensure that all edges of the first batch are sufficiently covered by tiles of the second batch.

After the study area has been cropped, it is time for the Watershed segmentation. This is an OTB algorithm that can be selected in the dropdown menu of the “Segmentation” algorithm. Then, the existing segment-ID field in the attribute table is deleted and a new field for the training data added. The user can proceed to select meaningful segments that represent the class of either terrace flat or terrace edge, whereby it is important not to select segments that span both classes, if any are remaining. It is better to have less training data that truly represents the characteristics of each class, rather than more training data which blurs the lines between the classes. Once the user has finished selecting and entering meaningful segments, the attribute table can be saved and is ready for the next step.

For the SAGA algorithm “supervised classification for grids”, the image that is to be classified is entered along with the shape layer containing the training segments. The output of this algorithm is a greyscale image containing the classes. Here, the layer can be formatted to contain classified colours. The user can chose colours for each class that make sense, and in this case, light green was again selected for the terrace flats and dark green for the terrace slopes. If this classification is to be layered over a different raster, the QGIS tool “Polygonize (Raster to Vector)” can be used to convert the classified raster into a shape file.

The user can map the terrace edges according to the classification results because the edge is always located between a terrace flat and a terrace slope. Once these edges have been mapped, the slope visualisation can be used in order to determine whether the edge belongs to a terrace of type one or type two according to the methodology described in chapter 5.1.5.

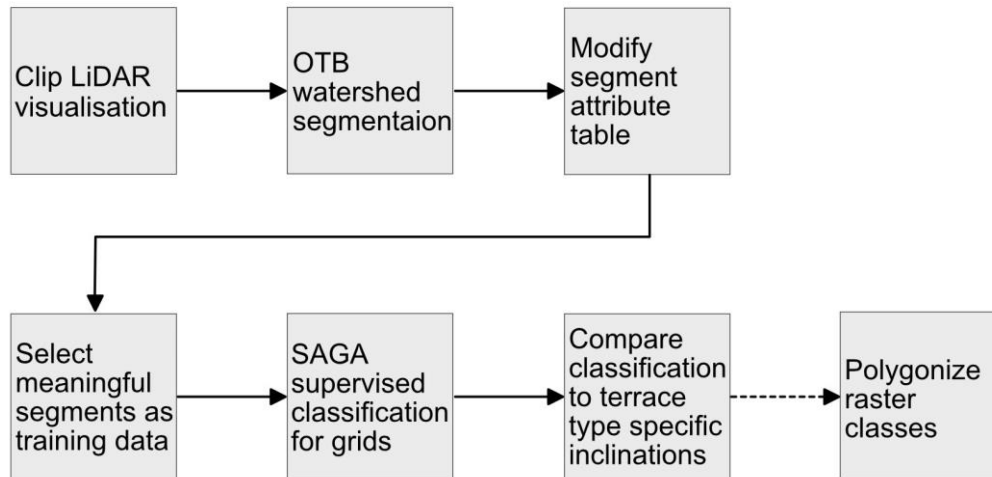


Figure xxvii: Flowchart of the final workflow (Pierina Roffler).

5.3. Semi-automation in the QGIS graphical workflow modeller

As was already mentioned in chapter 4.3.2.2, Orfeo Toolbox seems to have trouble processing temporary files. This poses a problem for the automation of the workflow with the QGIS graphical workflow modeller because the modeller ends the process chain automatically as soon as an algorithm is prompted to save the output. Hence, the workflow had to be automated in three steps.

The first step asks the user to enter the LiDAR visualisation, upon which it returns the Watershed segments. To speed up the processing time, it is advisable for the user to crop the LiDAR visualisation input to the desired study area first. The next step takes these segments, makes the necessary changes in the attribute table and returns a segmentation layer that is ready for the user to select relevant polygons and add a training class to them. The third and final step uses the original LiDAR visualisation, as well as the segments to which the user has entered training data and uses both to deliver the final classification. Figure xxviii shows screenshots of the graphical workflow modeller for each of the three steps.

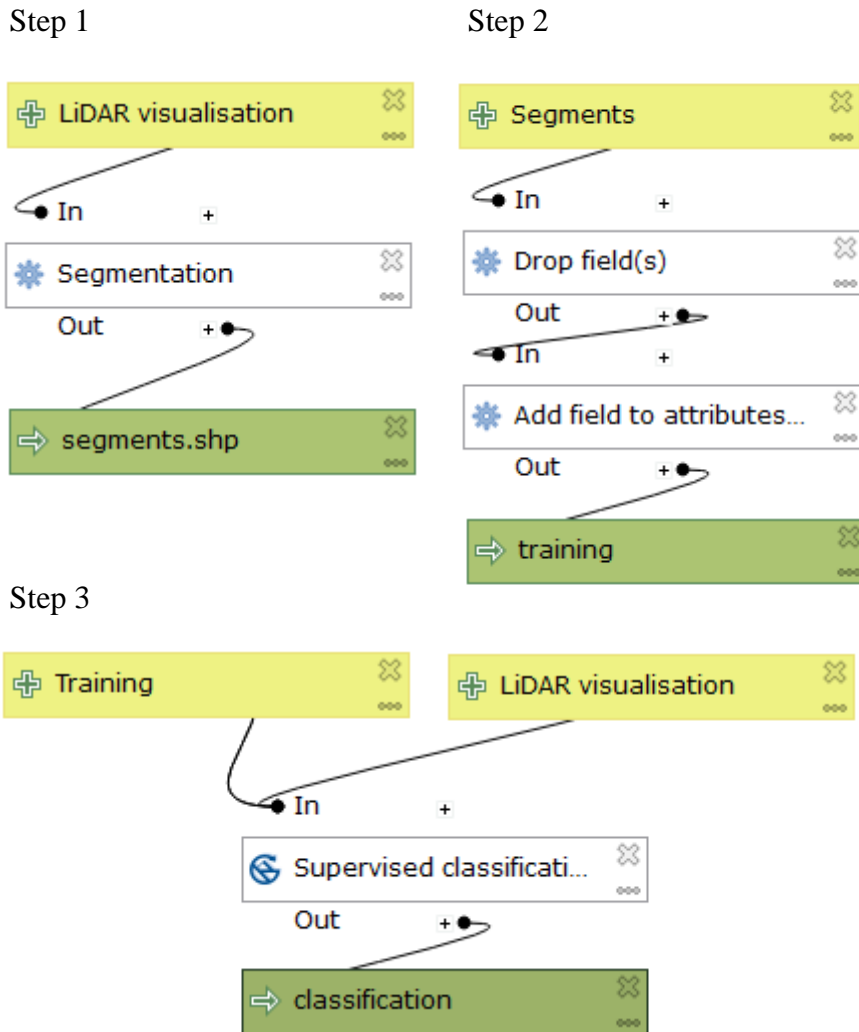


Figure xxviii: The three steps of the graphical workflow modeller (Pierina Roffler).

It has to be said that this particular GeOBIA workflow is quite user heavy, especially because the training segments need to be selected and entered manually. This makes it impossible to fully automate the workflow in the first place, and the addition of the third step was dictated by the inability of the Orfeo Toolbox to process temporary files. Even though the user heaviness of the workflow makes a completely automatic workflow impossible, it has the benefit of giving the interpreter full control over the entered training data. This means that the GeOBIA workflow does exactly what it is supposed to do: it supports the user without interfering with his or her expert knowledge.

5.4. Results

The result is a raster file that highlights potential terrace flats and slopes, and the border between the two classes is where the potential terrace edges are located

(Figure xxix).³⁶ In order to have an idea of the location of these edges in the field, mapping results were obtained and used courtesy of Angelika Abderhalden-Raba. The terrace edges were identified in aerial photographs, numbered and verified in the field (Raba 1996, 87). These mapping results were invaluable as a benchmark in order to verify the segmentation and classification results of the workflow.

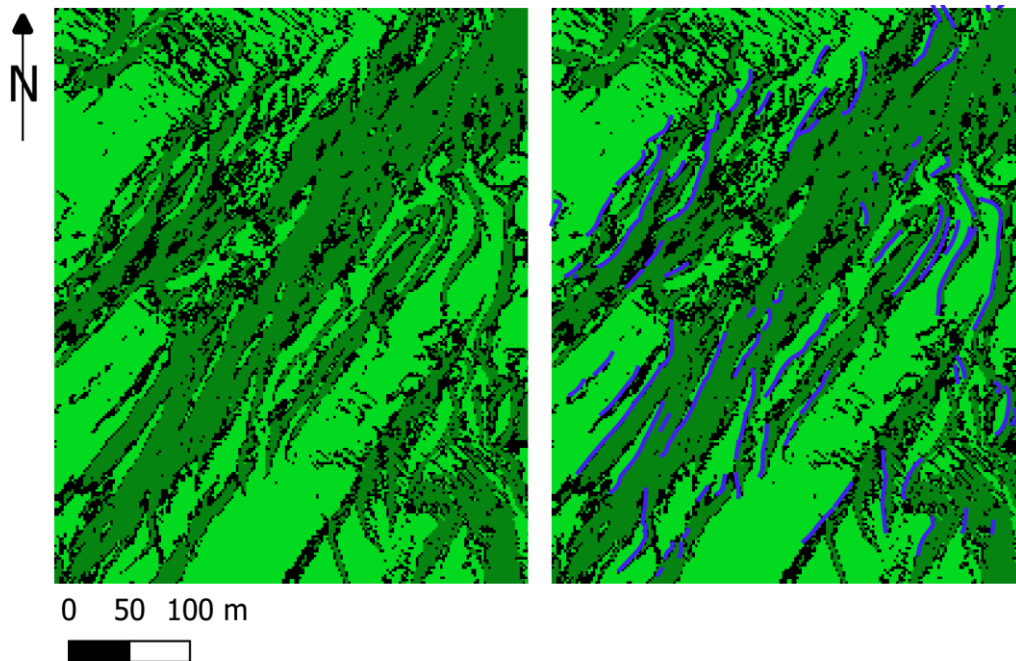


Figure xxix: The final classification result for a clipping of the upper study area. On the left hand side is the final classification in the format that an archaeologist would work with. For illustration purposes, the terrace edges that were mapped by Angelika Abderhalden-Raba were layered over the right image.

As can be seen in Figure xxix, the results of the developed GeOBIA workflow hold up against the mappings of Abderhalden-Raba that were used as a benchmark, as these fall right in between the light green (terrace flat) and the dark green (terrace slope) areas of the classification results. For a classification of the entire study area, please consult appendix ii.

The classification can be combined with the slope visualisation that has been filtered for the terrace type specific inclinations in order to evaluate whether the classified terraces are of type one or two (chapter 5.1.5). Figure xxx³⁷ shows the mapping results of Raba (1996) as a benchmark layered over the classification results of the lower study area as well as the terrace type specific flat inclinations

³⁶ QGIS layers “regular watershed classification no roads” and “ra85terrace”.

³⁷ QGIS layers “type 1“, “type 2“, “classification lower study area” and “ra85terrace”.

(yellow) and slope inclinations (red) for terrace types one (above) and two (middle). It becomes clear that the inclinations of terrace type one match the classification results much more accurately. Similarly, figure xxxi³⁸ shows the same situation for the upper study area, where it becomes apparent that the inclinations of terrace type two much more clearly represent the classification results. For a mapping of the terrace type specific inclinations of the entire study area, please consult appendices iii and iv.

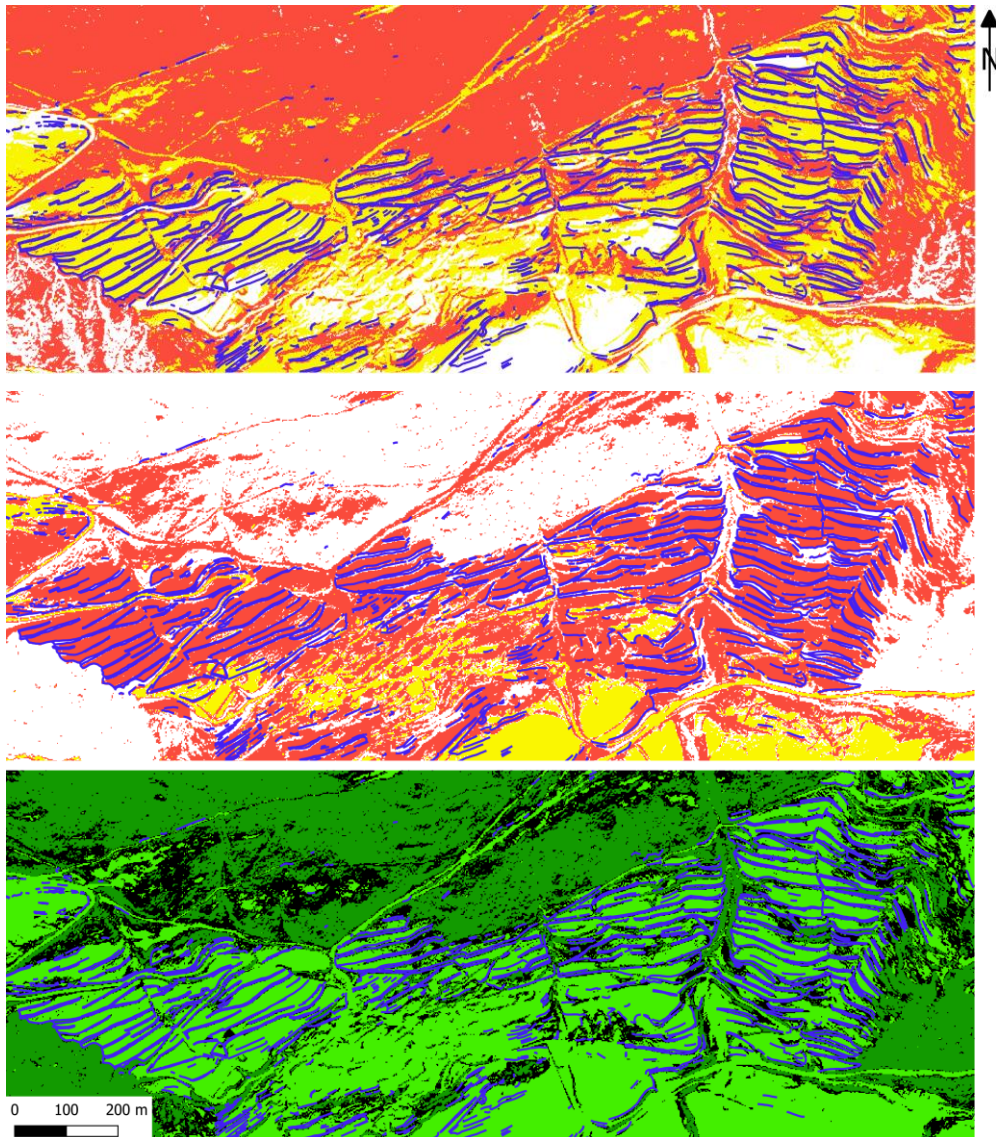


Figure xxx: The terrace type specific slope inclinations (yellow) and flat inclinations (red) for terrace type one (above) and two (middle) as well as the classification results of the lower study area. The mapping results of Raba (1996) are layered on top to serve as a benchmark.

³⁸ QGIS layers “type 1“, “type 2“, “regular watershed classification no roads” and “ra85terrace”.

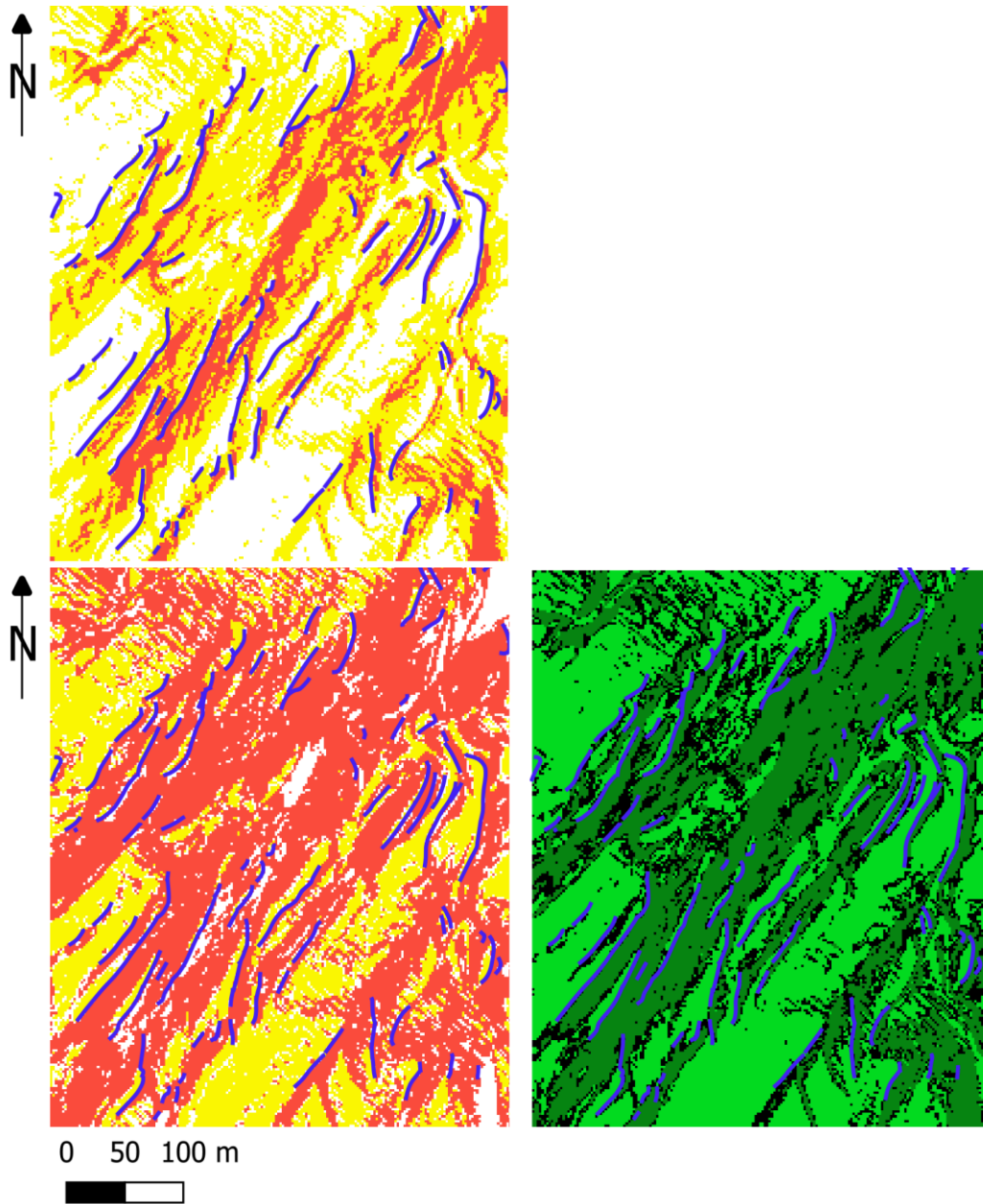


Figure xxxi: The terrace type specific slope inclinations (yellow) and flat inclinations (red) for terrace type one (above) and two (middle) as well as the classification results of the lower study area. The mapping results of Raba (1996) are layered on top to serve as a benchmark.

5.4.1. Transferability

Some experiments were carried out in order to find out whether training segments from one part of the study area could be used to classify a different part of the study area. This only works if there is an overlap between the two study area clippings. If there is no overlap, the classification comes out empty because there is no training data available to the classifier. By creating a slight overlap with the original study area clipping that contains the training data, the classified area can be extended. However, if there is no overlap at all, new training data needs to be added.

However, the values that were found to work best for the Watershed segmentation (all default except the depth threshold that needs to be changed from 0.01 to 0.05) work for both the upper and the lower part of the study area, and thus can be used for any clipping. Of course, using one set of training segments to classify all clippings would save time, but then again, reselecting suitable segments leads to better results because one can be sure that the most representative segments for the specific visualisation conditions of the clipping have been selected.

5.5. Discussion and Conclusion

The second aim of this thesis was to create a custom GeOBIA workflow for the heterogeneous landscape of the Lower Engadin that uses only FOSS applications and is user friendly for someone without programming skills. The first step of the testing phase was to evaluate the effectiveness of different LiDAR visualisations for the upper, as well as the lower part of the study area. The visualisations were created in the RVT 2.2.1 (Kokalj and Somrak 2019; Zakšek *et al.* 2011) following the recommendations of Kokalj and Hesse 2017. For the lower study area, hillshades work best while for the upper, more diffuse study area, slope worked best. It was decided to work with the slope visualisations for both areas because this visualisation provides the most consistent results for all terrain types and lighting conditions within the study area. As discussed in chapter 5.1.1, the reason for this is that the terraces in the lower study area are all oriented more or less in the same direction while those in the upper study area are more irregular and located in more complex terrain. Hillshade visualisations are susceptible to terrain and lighting, while the slope visualisation is not. Thus, the slope visualisation is capable of producing very consistent results for both parts of the study area, regardless of the terrain morphology.

Different smoothing, segmentation and training parameters or options were tested, and finally, it was decided that the best results were obtained by an unfiltered slope visualisation, a Watershed segmentation and the manual input of training fields via the segment attribute tables.

The final workflow works with a combination of algorithms from both the OTB and SAGA plugins in QGIS. The semi-automation of the workflow with the help of the QGIS graphical workflow modeller turned out to be difficult as OTB does not handle temporary files and the graphical workflow modeller ends the process

chain as soon as an output is saved. Finally, a three step workflow was achieved in the graphical workflow modeller.

Closing the loop to the research question: What are the elements that an effective FOSS GeOBIA workflow for heterogeneous and linear archaeological objects needs to contain? The answer is:

- cropping the LiDAR visualisation to the desired area;
- segmentation using the Watershed segmentation algorithm;
- modifying the attribute table of the segmentation layer to allow for the ...
- selection of training polygons for the...
- supervised classification algorithm and finally
- the comparison between the classification and the terrace type specific inclinations to evaluate the type of terraces that have been classified.

If needed, the resulting raster areas representing possible geo objects can be converted into vector polygons for further mapping.

Unfortunately, it was not possible to consider neighbourhood relationships between the image objects as the tested FOSS applications do not offer a solution for these (yet). Nonetheless, the designed workflow produced classification results that held up against the mappings of terrace edges (Raba 1996) that were used as a benchmark.

In conclusion it can be said that by systematic experimentation and testing of modifications within the range of possible approaches, an efficient and user-friendly FOSS workflow for GeOBIA was created. In order to assess the benefits of the resulting classification, as well as the user friendliness, a survey was carried out. This survey is the topic of the following chapter.

6. The benefits of a semi-automatic image analysis workflow

The third aim of this thesis was to find out whether a semi-automatic classification could be beneficial to the user or whether the LiDAR visualisation on its own is still the most intuitive basis for manual classification. The third research question was the following: Does the developed workflow deliver results that save time and support the human interpreter?

In order to evaluate whether or not the semi-automatic classification workflow offers support to the interpreter, feedback about the usefulness of the classification was needed. This was accomplished by asking a group of users to map terrace edges with the help of a hillshade and a classified image. They were also asked directly whether they preferred working with the visualisation or with the classification. This feedback was obtained by sending out a survey questionnaire.

6.1. Survey setup

The survey questionnaire showed a hillshade visualisation of the LiDAR DTM alongside the classification result of the exact same area (Appendix v). Because some participants were English speaking and some were German speaking, the questionnaire was created in both languages. The survey participants were informed that the light green areas within the classification were indicators for terrace flats while the dark green areas indicated terrace slopes, before asking them to draw all the terrace edges that they saw. The participants were told that it did not matter whether they marked the terrace edges on the hillshade or on the classification. Next, the participants were asked to answer two questions:

- 1) Did the classification help you with your decision on the location and extent of the terrace edges?
- 2) Did you prefer working with the hillshade, the classification, or with the combination of both?

Two groups participated in the survey; one of which consisted of students who had taken part in at least one field campaign of the TERRA project and thus knew the landscape and had an idea of what an agricultural terrace looks like, and a second group of people who were all laypersons. Initially, only the first group was planned but after the first few feedbacks from TERRA participants came in, it was found

that members of the specialised group sometimes used their prior knowledge of the area and the agricultural terraces, leading them to question some of their decisions (for more details see chapter 6.3.1). The idea emerged that perhaps someone with absolutely no prior knowledge would perform a more straightforward and unbiased analysis, and for this reason the second group was added.

It was decided that the images should contain as little geographical information as possible as the aim of the survey was simply to see whether the classification aided in the detection of structures or not. However, it soon became very clear that an indication of the scale of the image was indispensable for the user to have a reference of the size of the terraces within the images. The TERRA participants only received the survey as it could be expected of them to know what an agricultural terrace is and looks like, and how a hillshade is to be interpreted.

The participants of the second group that had no prior knowledge of the subject were given a bit of background information. More specifically, they were told what an agricultural terrace is and given an example of the well-defined terraces of the lower study area as hillshade and classification (figure xxxii). They were also told that the example terrace cluster was only for illustration purposes and not to scale with the area on the survey questionnaire, and they were informed that the area that they were asked to analyse is more eroded and thus the objects are more diffuse.

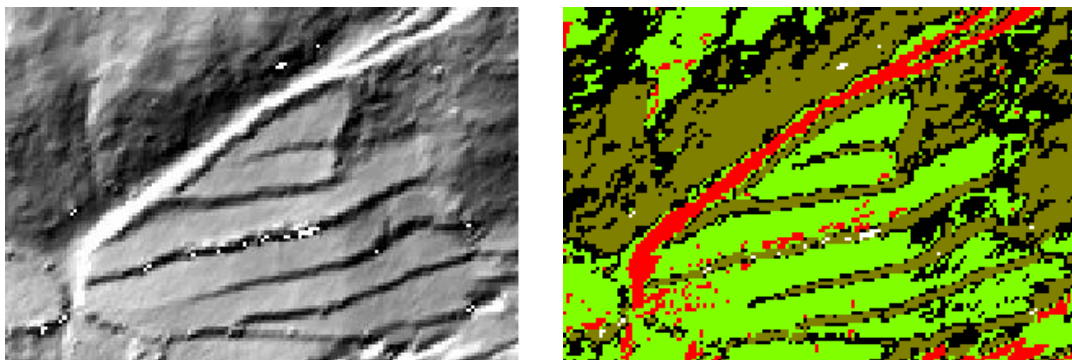


Figure xxxii: The example terrace cluster that was given to the participant group without prior knowledge as hillshade (left) and classification (right). (DTM: Bundesamt für Landestopografie (2019), visualisation created in RVT2.2.1 (Kokalj and Somrak 2019) by Pierina Roffler).

Group one, the TERRA participants consisted of 7 students from both Leiden University and the University of Zurich. Group two, the participants that had no prior knowledge was formed of 7 individuals who have not studied archaeology.

In 1993, Nielsen and Landauer researched the ration between benefits and costs of using various numbers of software evaluators to identify usability problems and

came to the conclusion that after five users this ratio sinks dramatically (Nielsen and Landauer 1993, 212). These findings were confirmed by Brandsen *et al.* (submitted) who found that in their user study, not many new issues were identified by new users after the fifth user evaluation (Brandsen *et al.* submitted). The researchers go on to state that perhaps, the ideal size of a user group is five users per user category (Brandsen *et al.* submitted). For this reason, the seven users per user group that were questioned in this thesis seem to be adequate in order to identify a wide range of issues.

6.2. Limitations of the survey

The author of this thesis has learnt a great deal about the way survey questionnaires need to be designed during the process of this thesis. A number of mistakes were made in the setup of this survey that can be avoided in the future.

The first oversight was the omission of the scale bar in the first version of the survey questionnaire. This led to one candidate having different conditions as compared to the rest of the group so that the result was inadmissible and had to be discarded. In addition, it turned out that the explanation of the exercise was not clear enough, leading to some candidates circling the terrace flats or slopes instead of marking the edges as a line. These two lapses are very easy to avoid in future versions of the questionnaire.

This survey was very qualitative, asking participants about their thoughts by using questions that left room for very detailed answers. These answers delivered valuable information about the way participants felt about the two image options and what their insecurities were. However, they are more difficult to quantify compared to answer sheets with check boxes.

Upon comparing the results against the mapping results of Raba (1996), it was soon realised that a point system for detected, undetected and wrongly detected terraces is problematic. The reason for this was that candidates often marked longer terraces that combined several shorter ones of Raba (1996), and other times they only marked a part of a terrace edge that was defined by Raba (1996). The only way to really quantify these results would be to count the millimetres of edge markings done by the candidate that correspond to the mapping results of Raba (1996). This problem is, again, the result of the very qualitative nature of the survey. In order to

truly quantify the answers, the candidates would have to be given small image snippets that either contained or did not contain a terrace edge, asking them to check yes or no boxes in the process.

6.3. Survey results

The results showed quite a large span of different answers. It was also found that there are not all too many differences in the answers given by the members of the two groups. In both groups there were individuals who had difficulties with the scale of the provided images, leading them to classify terraces that would in reality be over 400 meters long. Similarly, both groups contained individuals who circled the flats or slopes instead of marking the edges as a line. The conclusion that has to be drawn from these findings is that the instructions on the survey should have been more specific about the preferred format of the results.

As was mentioned in chapter 6.2, it is difficult to quantitatively assign points for detected, undetected and wrongly detected terraces as the extents of the edges that were marked by the participants varied greatly. For this reason, the analysis of the mapping results was based on the subjective impression of the author. In the following two sections, the results of both specific groups will be presented.

6.3.1. Group one (TERRA participants)

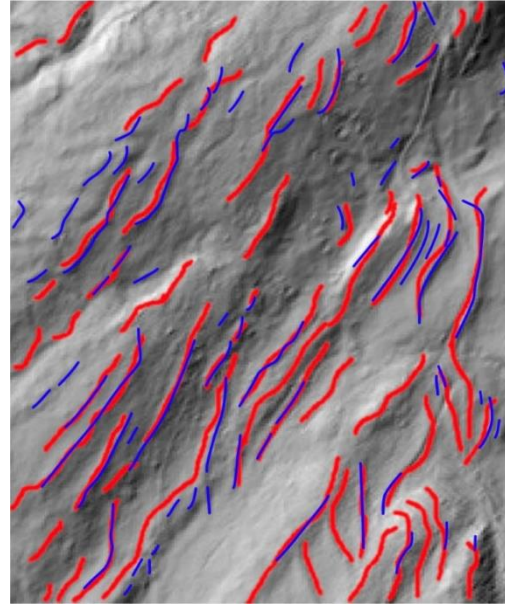
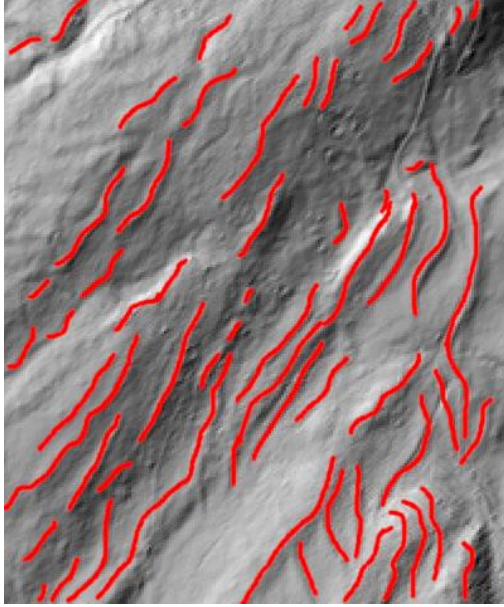
Two individuals from this group had difficulties with the scale of the images. It must be said that one of these two individuals was the first one to send the results back and it was thanks to this individual's interpretation that it was realised that a scale indication is indispensable. This means that all other participants received a corrigendum containing a scale bar and thus had different conditions for completing the survey. For these reasons, the classification of the first individual cannot be counted.

One individual of this group circled terrace flats instead of marking the edges and as was already mentioned in chapter 6.2, the lesson to be learnt here is that in the future, concise instructions must be given to test people.

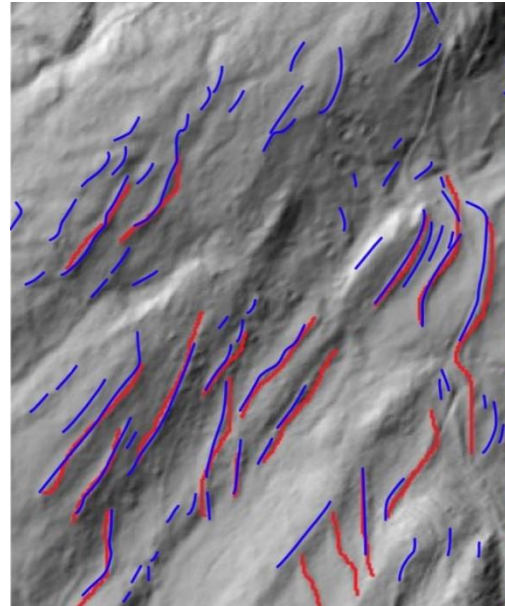
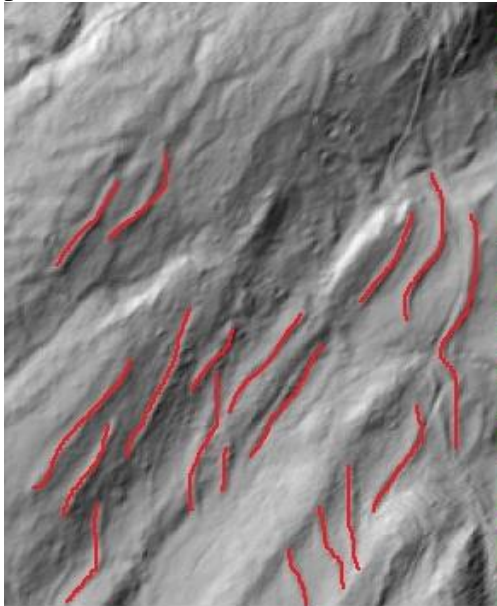
The following table, table ix, summarises the mapping results compared to those of Raba (1996). On the left is the result as returned by the participant, while on the right is the same result with an overlay of the edges mapped by Raba (1996).

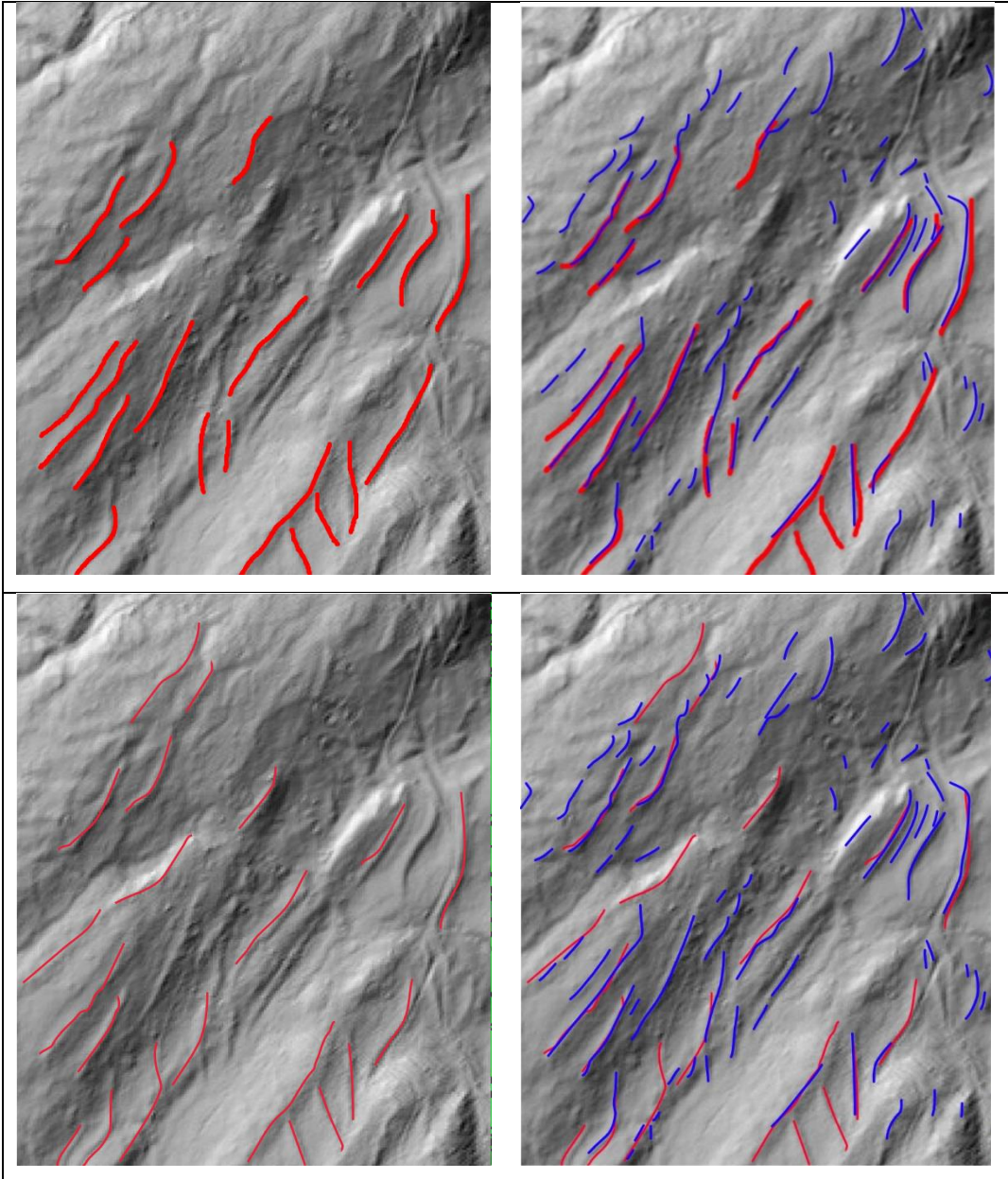
Table ix: The mapping results returned by members of group one (left). These results were compared to the edges that were mapped by Raba 1996 (right).

This participant mapped a lot of the terraces correctly but at the same time, mapped too many terraces overall.

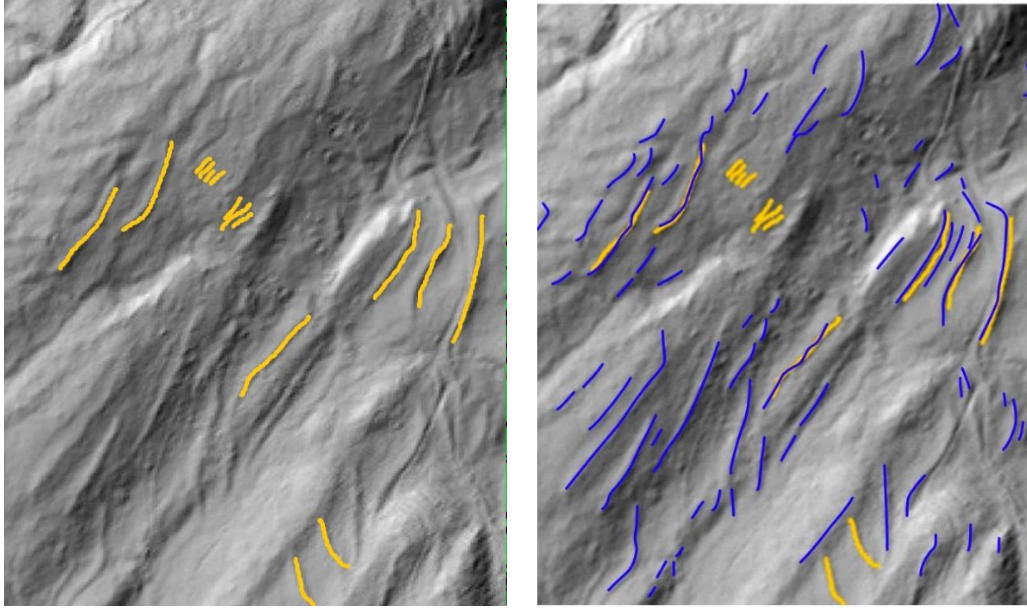


The following three participants placed almost all their terrace edges in the correct places, but missed some.

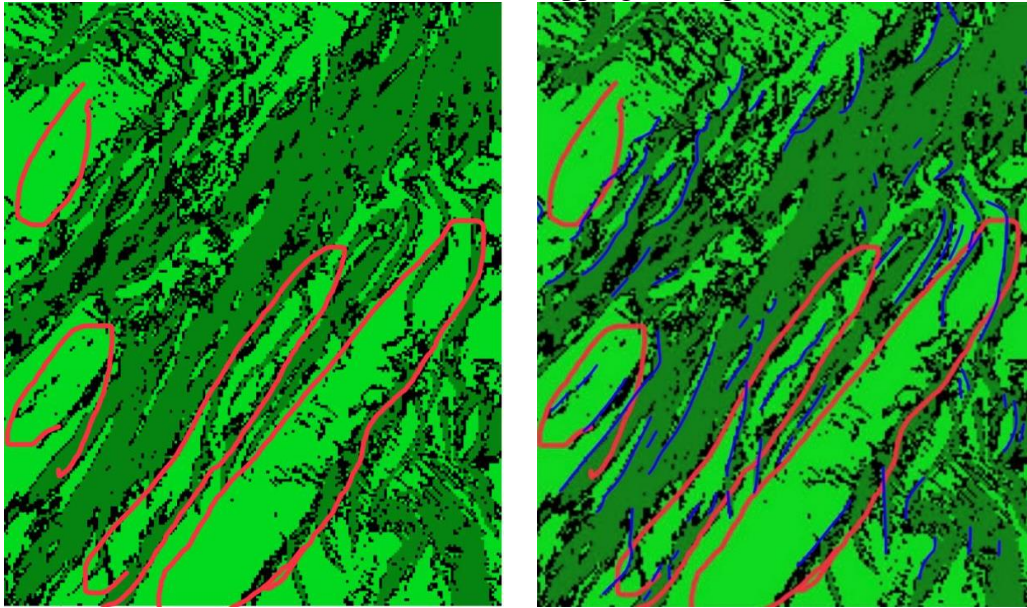




This participant missed quite a few terrace edges.



This participant had difficulties with the scale of the objects in the images and chose to circle the terrace flat instead of mapping the edges.



Of those participants who worked in the correct scale, four managed to map the majority of the terrace edges located within the images, although one of the three had the tendency to map too many terraces overall. One participant only located a small part of the terrace edges.

In addition to the classification exercise, the participants were asked the two questions;

- 1) Did the classification help you with your decision on the location and extent of the terrace edges?
- 2) Did you prefer working with the hillshade, the classification, or with the combination of both?

For the first question, six out of seven people stated that the classification helped with their decision. Some people already mentioned that the combination of both the hillshade and the classification was helpful to them. This leads to the answers to the second question. Five people stated that they used a combination of both the hillshade and the classification, one person stated that they preferred working with the classification but went on to say that the combination of both methods seems important to them. One person preferred working with the hillshade, stating that they were used to working with these kinds of visualisations and that they appeal to them more than a colour-code. For the full answer statements in anonymised form, please consult appendix vi.

One person stated that they would be careful defining some of the image objects as intentional terrace edges, but rather as the product of geological movement of the hillside. This person also noted that they would not address the flats and slopes defined by the classification as terraces, but interestingly enough, if the edges mapped by this individual are transferred from the hillshade onto the classified image, they match the edges that are suggested by the classification (figure xxxiii).

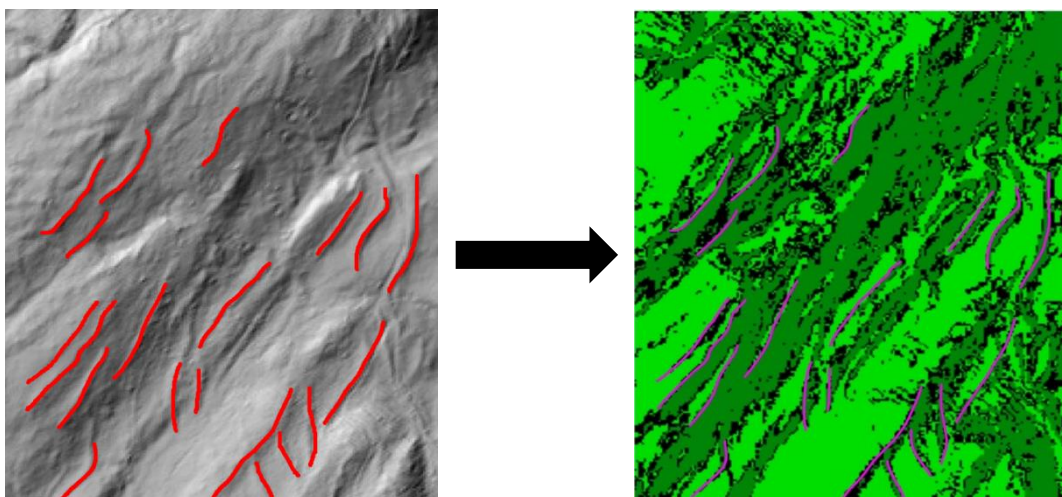


Figure xxxiii: This test person stated that they would not address the flats and slopes in the classification as terraces, but once the mapping results are transferred from the hillshade onto the classification, the edges all lie on the border between the light green terrace flats and the dark green terrace slopes (DTM: Bundesamt für Landestopografie (2019), visualisation created in RVT2.2.1 (Kokalj and Somrak 2019) by Pierina Roffler).

Another participant stated that the field surveys showed that terrace flats are not perfectly horizontal and planar, but rather flattened terrain, and that the classified image more clearly showed the relationships between the objects. Two people stated that they found the recognition of terrace edges on the hillshade to be easier, but that the classification gave a clearer picture of the extent and shape of the terrace edges. Two other individuals noted that the combination of different sources of information and techniques always lead to better and more sound decisions.

Because the majority of this test group stated that the combination of both the LiDAR visualisation and the classified image was very helpful, it may be worth experimenting with the layering of the classification as a semi-transparent layer over the LiDAR visualisation. One individual even suggested layering the classification over a three-dimensionally visualised LiDAR in a 3D GIS to further aid the object detection.

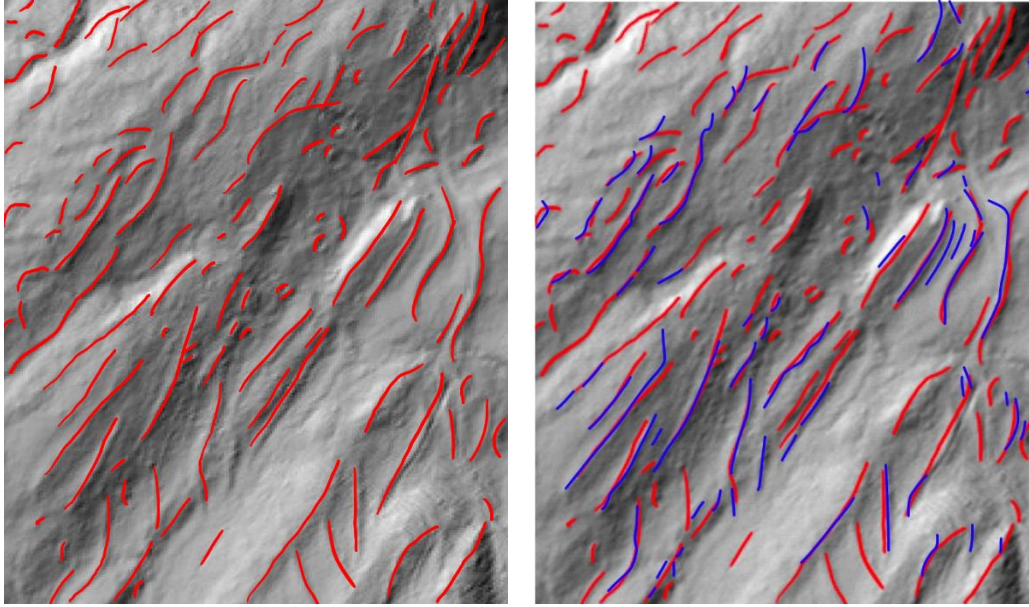
6.3.2. Group two (no prior knowledge)

In this group, one individual had difficulties with the scale of the image objects, marking only a few very large terraces in the hillshade. One individual circled the terrace slopes instead of marking the edges but this, again, could have been avoided with clearer instructions by the author. Just like the results from group one, the classifications of the participants were cross checked against the mapping results of Raba (1996). The following table, table x, summarises the results of group two. Again, the left is the result as returned by the participant, while on the right is the same result with an overlay of the edges mapped by Raba (1996).

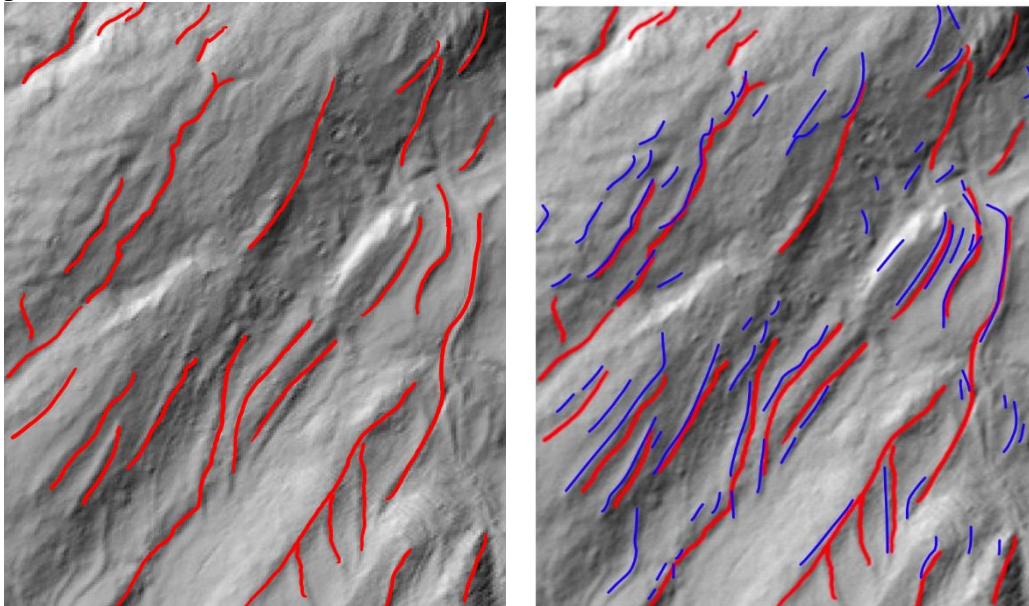
Only one participant in this group had difficulties with the scale of the image objects. Perhaps the sample images that were given to this group prior to the survey were helpful. One participant circled the terrace slopes rather than marking the edges as a line, but managed to identify a good portion of the slopes correctly, and another person missed quite a few of the terrace edges. Four people managed to identify a large portion of the edges, missing only a few, although one of them mapped too many edges overall.

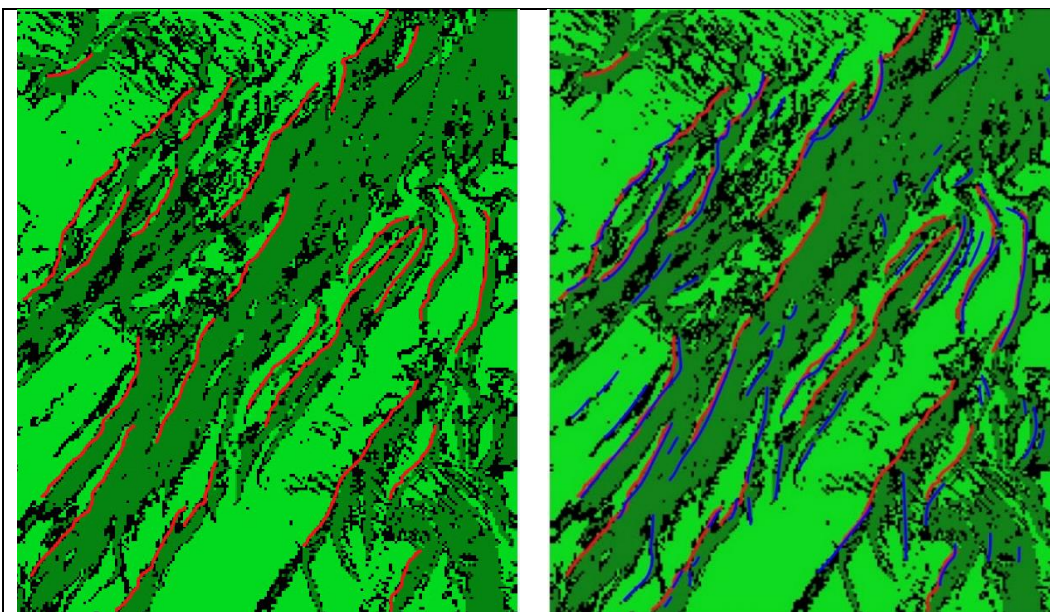
Table x: The mapping results returned by participants of group two (left). These results were compared to the edges that were mapped by Raba 1996 (right).

This participant mapped a lot of the terraces correctly but at the same time, mapped too many terraces overall.

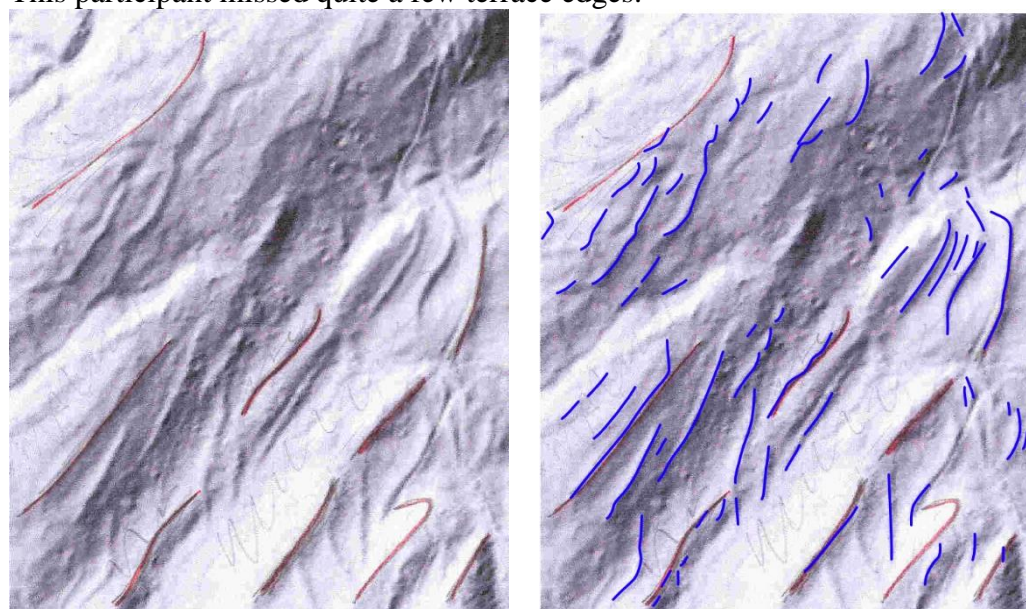


The following two participants placed almost all of their edges in the correct places, but missed some.

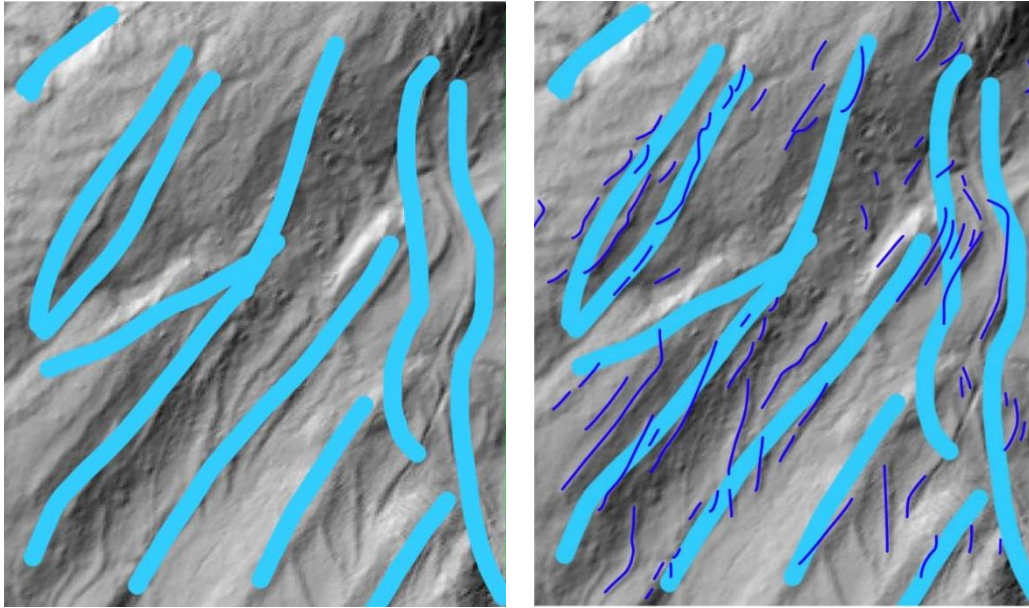




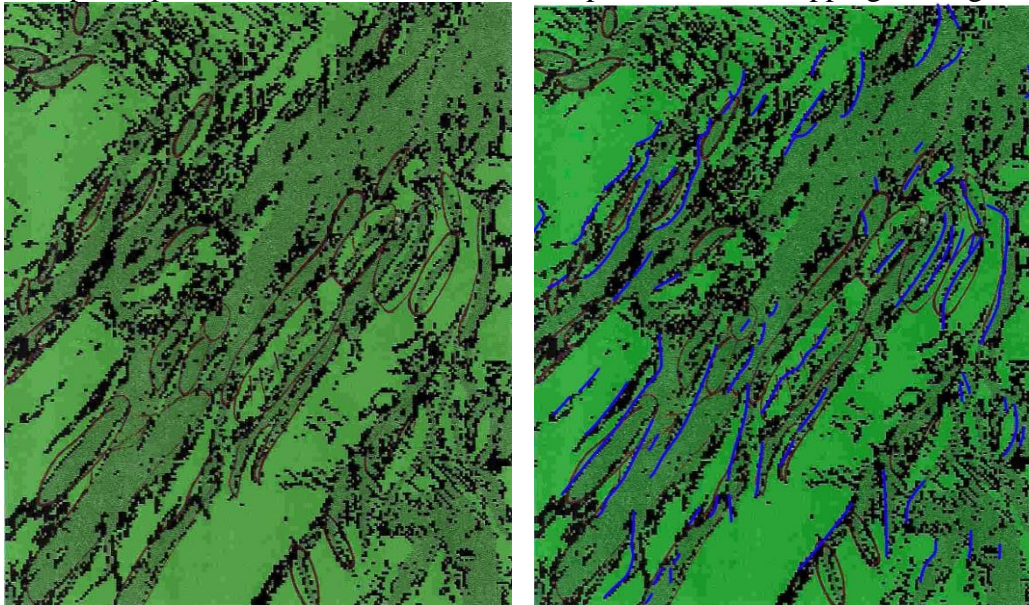
This participant missed quite a few terrace edges.



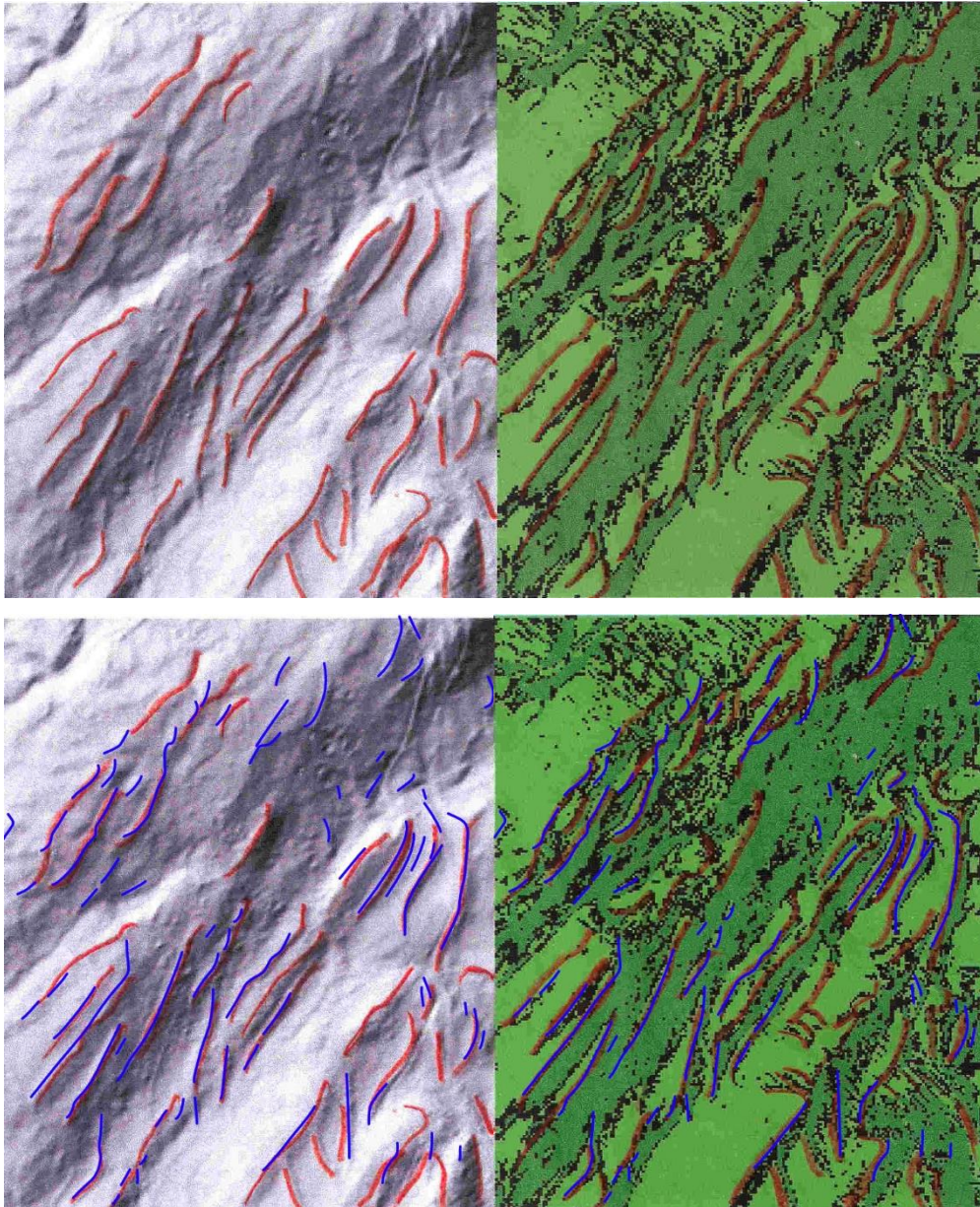
This participant had difficulties with the scale of the image objects.



This participant chose to circle the terrace slopes instead of mapping the edges.



This participant mapped both the hillshade and the classified image. They mapped most of the terrace edges correctly, in the hillshade there are some missing, in the classification there are a few too many. The reasons for processing both the hillshade and the classification will be discussed shortly.



This group was also asked whether the classification helped with the decision on the location and extent of the terrace edges, as well as whether the participants preferred working with the hillshade, the classification or with a combination of the both.

To the first question, all seven participants answered that indeed, the classification helped with the decision on the location and extent of the terrace edges. Five people

stated that they worked with the combination of both the hillshade and the classification, while two people stated that they only used the classification.

Two people stated that the classification helped confirm their initial classification in the hillshade, one person noted that they began the exercise by mapping the hillshade and using the classification for verification purposes but realised that they had switched to using the classification as a starting point after just a few minutes, followed by consulting the hillshade for confirmation and a plausibility check (figure xxxiv). Two people stated that the classification indicated the presence and the extent of a terrace more clearly than the hillshade visualisation. Again, please consult appendix vi for the full answer statements.

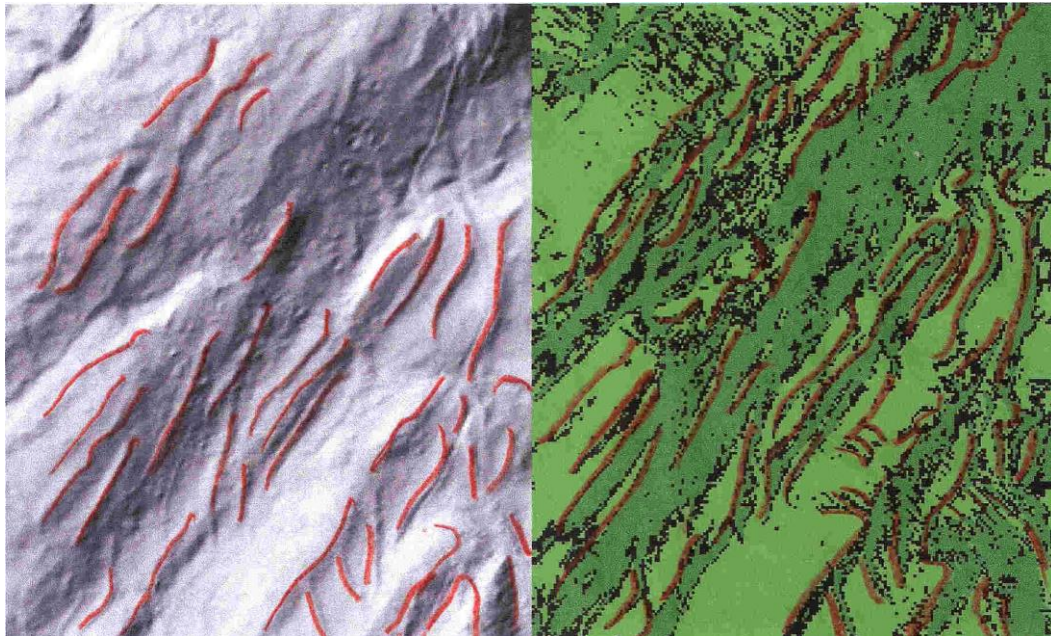


Figure xxxiv: This participant stated that they had switched from using the classification to verify their results within the hillshade to using the hillshade to verify their results in the classification (DTM: Bundesamt für Landestopografie (2019), visualisation created in RVT2.2.1 (Kokalj and Somrak 2019) by Pierina Roffler).

6.4. Comparison of the results generated by the two user groups

Interestingly, it seemed that users in group one were more reluctant to trust the classification. The best example for this reluctance is the participant that stated they would not address the flats and slopes in the classification as terraces but ultimately, the edges placed by this individual correspond well to the classification (figure xxxiii). Perhaps because users from groups two had no prior knowledge and were not used to working with a LiDAR visualisation, they had no other choice but to

heavily rely on the classification. In any case, the results of both groups are highly comparable. In both groups there were users who had trouble with the scale of the image and in both groups some users mapped too many terraces while some users missed quite a few terraces. It is interesting to see that apparently, the prior knowledge of the study area and of archaeology in general that participants in group one possessed did not give them any significant advantage when it came to mapping terrace edges.

This is an interesting result that is in line with a study conducted by Herfort *et al.* (2018), where the researchers gave a group of secondary school children as well as a group of undergraduate and graduate students of Geography at Heidelberg University three different tasks of differing complexity to perform on a LiDAR point cloud (Herfort *et al.* 2018, 78). The results of this study showed that the two more straightforward tasks were of the same complexity for any user, regardless of their prior knowledge or experience (Herfort *et al.* 2018, 79). These findings stand in a stark contrast to the opinion of Casana (2020), who advocates strongly for expert-led remote sensing investigations rather than the use of crowd-sourcing and citizen science, stating that most of these efforts to include the general public produce data that “have so much noise as to be analytically useless” (Casana 2020, 98).

Contradictory to Casana (2020), Verschoof-van der Vaart *et al.* (2020), who compared the results of citizen researchers to a machine learning approach for detecting barrows, charcoal kilns and Celtic fields in LiDAR visualisations of the Veluwe area in the Netherlands, found that citizen researchers outperform the machine learning workflow, especially in terms of precision³⁹ (Verschoof-van der Vaart *et al.* 2020, 16). The researchers state that this may be because the citizen researchers were given two different LiDAR visualisations and thus perhaps more easily determined possible detections as being objects of confusion (Verschoof-van der Vaart *et al.* 2020, 16).

The results generated by the user study of this thesis would also contradict the opinion of Casana (2020) as the individuals of group two who had no prior knowledge produced classification results that were of the same quality as those

³⁹ In precision and recall analyses, precision is the sum of true positives divided by the sum of true and false positives or, in other words, the amount of selected items that are relevant.

generated by the specialist users in group one. It has to be said that the individuals of group two received a more extensive introduction (examples of a clearly defined terrace cluster as a hillshade and a classification for referencing purpose). Considering the findings of Herfort *et al.* (2018) that the complexity of the task is a more influencing factor on performance than prior knowledge (Herfort *et al.* 2018, 79), perhaps this additional information made the task for users in group two a less complex endeavour because they had a reference for what they were actually looking for.

6.5. A note on bias and time savings

As already mentioned in chapter 6.3.1, some participants of group one used their prior knowledge of the area and of the agricultural terraces for their mapping decisions. It was interesting to see that the individuals of group two generally mapped more terraces than the individuals of group one, perhaps precisely because they did not have any prior bias about the morphology and the location of agricultural terraces. In the future, it could be interesting to conduct a systematic survey about the bias of archaeologists and whether or not this bias can be eliminated by the addition of a classification.

13 of the 14 survey participants stated that the classification was helpful to them. It takes just about 40 seconds to run the three processing steps in the workflow modeller for a smaller study area and a little under 8 minutes for a larger 500x500 tile. In addition, it takes the interpreter some time to select and enter suitable training data, but even so, the full workflow should take no more than 5-10 minutes to complete. This shows that with minimum time and effort the interpreter can create a classification of the desired study area that aids him or her with the mapping process, even if it is just to draw the attention of the interpreter to potential archaeological objects within the LiDAR visualisation.

6.6. Discussion and Conclusion

The third aim of this thesis was to find out if the result of the semi-automatic classification workflow could be beneficial to interpreters, or whether the LiDAR visualisation on its own is still the preferred basis for manual classification. The question corresponding to this aim was:

Does the developed workflow deliver results that save time and support the human interpreter?

In order to evaluate whether the classified image that was achieved with the semi-automatic classification workflow offers support to the interpreter, a total of 14 survey participants were asked to perform a manual classification using a hillshade visualisation and a classification of the same area, before being asked the following two questions:

- 1) Did the classification help you with your decision on the location and extent of the terrace edges?
- 2) Did you prefer working with the hillshade, the classification, or with the combination of both?

The survey participants formed two groups. Group one was composed of seven students of the Universities Leiden and Zurich, who had all taken part in at least one TERRA campaign and thus knew the area and had an idea about the morphology of an agricultural terrace. Group two contained seven laypersons. The vast majority of all survey participants preferred to work with a combination of the classification and the hillshade visualisation. One person preferred working with the LiDAR visualisation and two people worked exclusively with the classification.

It seemed that the participants in group one who had prior knowledge were more distrustful of the classification, even though their mapping results corresponded well with the classification results. Overall, the results from both groups are highly comparable, neither of the user groups performing better than the other. These findings go along well with the findings of Herfort *et al.* (2018), namely that it is the difficulty of the task that is the deciding factor for the performance of the users rather than experience or prior knowledge (Herfort *et al.* 2018, 79).

13 out of 14 survey participants stated that the classification aided them in determining the exact extent and shape of the terrace edges, or that it was easier to work with two colours than a greyscale, and some stated quite rightly that the combination of different sources of information and techniques always lead to better and more sound decisions. One person even switched their methodology after a few minutes and instead of using the classification to verify the edges in the hillshade, used the hillshade to confirm the edges in the classification.

These results show that the resulting classification from the semi-automatic image analysis workflow was very beneficial to the users. Time-wise, the processing algorithms of the graphical workflow modeller takes around 40 seconds to complete for smaller study areas and just under 8 minutes for an area of 500x500 pixels. Some additional time needs to be spent on the selection of training data but even so, the workflow should not take longer than 5-10 minutes to complete.

Overall, the workflow proves to be an uncomplicated and effective way to greatly aid the human image interpreter.

7. Conclusion and outlook

The technical advances of the past years in the field of remote sensing have led to the creation of large amounts of datasets with a high temporal, spectral or spatial resolution. Contrary to the technological advances in the field of remote sensing, the interpretation of these datasets in archaeology is still largely a manual undertaking. However, the problem is that manually interpreting all this remote sensing data is a very time consuming task and in some cases, such as in the case of hyperspectral data, the human eyesight is incapable of processing the full range of information. The semi-automation of image analysis is one solution to the aforementioned issues. Critics of semi-automatic image analysis workflows state that a human interpreter has the benefit of experience and flexibility that a computer algorithm will never be able to replace. It is important to state here that it is not the aim to replace human interpreters, but rather to support them with substantial time savings or by computing additional layers of information.

Several different (semi-) automatic image analysis approaches were presented in chapter 2. Studies have shown that object-based image analyses work better for heterogeneous and linear objects than pixel-based approaches. Because the results of this thesis were applied to the terraced landscape of the Lower Engadine in Switzerland, a landscape that contains many heterogeneous and linear objects such as agricultural terraces, roads and drainage/irrigation ditches, it was decided to focus on Geographic Object-Based Image Analysis (GeOBIA). More specifically, it was decided to develop a GeOBIA workflow for LiDAR visualisations of the terraced landscape of the Lower Engadin, Switzerland.

It was the first aim of this thesis to provide an overview of the existing free and open-source (FOSS) GeOBIA applications and to assess the user friendliness, effectiveness and suitability for the study area of each programme. Because a large part of archaeologists presently does not have programming skills, it was important that the tested GeOBIA solutions have a Graphical User Interface (GUI). The second aim of this thesis was to create a custom GeOBIA workflow for the heterogeneous landscape of the Lower Engadine. The workflow made use of only FOSS applications in order to promote accessibility, transparency and reproducibility of the research. The third aim was to find out whether a semi-automatic image analysis workflow could be beneficial to the user or whether the

LiDAR visualisations on their own are still the most intuitive basis for manual classification. These aims correspond to three research questions:

- Is there an open source solution for GeOBIA available with a Graphical User Interface (GUI) that is user friendly, does not require additional coding and will prove through systematic testing to be capable of classifying the heterogeneous and linear features within the terraced landscape of the Lower Engadine?
- What are the elements that an effective GeOBIA workflow for heterogeneous and linear archaeological objects needs to contain?
- Does the developed workflow deliver results that save time and support the human interpreter?

In order to answer these aims and research questions of this thesis, a number of methodological steps were undertaken. In the first step, the Digital Terrain Model (DTM) of the study area was visualised in eight different ways using the Relief Visualisation Toolbox version 2.2.1 (Kokalj and Somrak 2019; Zakšek *et al.* 2011). These visualisations were then imported into different FOSS applications with a GUI such as SAGA GIS or QGIS, as well as into the two popular proprietary applications eCognition and ERDAS IMAGINE. In each of the tested software solutions, a GeOBIA workflow was carried out in order to assess the user friendliness of the programme, but also its effectiveness and suitability. The reason for including the two popular proprietary applications was to understand their popularity and the reason why so many researchers still prefer them over a FOSS solution. During the software testing processes, the necessary steps of the GeOBIA workflow became more and more apparent.

After testing the different GeOBIA applications, the custom GeOBIA workflow for the terraced landscape of the Lower Engadine was developed. This step involved testing different LiDAR visualisations, pre-processing steps, segmentation algorithms and training data input methods, comparing the different classification outcomes in order to choose the most suitable combination of algorithms.

Finally, the effectiveness and accuracy for the resulting workflow was assessed by comparing the resulting classification with the manual mapping results of the study

area. Additionally, a survey was conducted in order to gain feedbacks about whether or not the classification results are beneficial to human interpreters.

The first research question asked if there is an effective, open-source solution with a GUI for GeOBIA available that is user friendly, does not require additional coding and proved through systematic testing to be capable of classifying the heterogeneous and linear features within the terraced landscape of the Lower Engadine. This question can be answered positively: SAGA GIS is a FOSS, intuitive and user friendly application. It does exactly what is necessary for an effective GeOBIA workflow, not more and not less. For the custom GeOBIA workflow it was decided not to use the standalone version of SAGA but rather the QGIS plugin, as this could be combined with the OrfeoToolbox plugin in order to have a broader range of functionalities available. Another benefit of implementing the workflow in QGIS is that this programme offers a graphical workflow modeller for the automation of the process chain, further promoting user friendliness.

The second research question asked what the elements are that an effective FOSS GeOBIA workflow for heterogeneous and linear archaeological object needs to contain. The answer to this question was found by systematic experimentation and testing, through which a six step workflow was defined. This workflow contains 1) cropping the LiDAR visualisation to the desired area, 2) segmentation using the Watershed segmentation algorithm, 3) modifying the attribute table of the segmentation layer to allow for 4) the selection of training polygons and, finally, 5) a supervised classification algorithm. The classification can then be 6) compared to the mapping results of terrace type specific slope inclinations in order to assess whether the mapped results in the classification are terraces of type one or two. An optional seventh step can be added: 7) converting the classes from the raster file into vector polygons. The workflow was implemented in the graphical workflow modeller as a three step processing chain.

Finally, the third research question asked whether the developed workflow delivers results that save time and support the human interpreter. The conducted survey showed that the vast majority of participants felt that the classification supported them in their mapping decisions, stating that the classification specifically aided them in determining the exact extent and shape of the objects. Time-wise, the processing chain takes around 40 seconds to complete for smaller study areas and

just under 8 minutes for an area of 500x500 pixels. Even when taking into consideration the time spent on the manual selection of training data, the complete workflow should take no longer than 5-10 minutes. That being said, with minimum time and effort the interpreter can create a classification of the study area that aids with the mapping process, even if it is just to draw the attention of the interpreter to potential archaeological objects within the LiDAR visualisation. In addition, the workflow still requires substantial user inputs, meaning that the human experience and flexibility, which critics fear will be lost in semi-automatic image analysis workflows, are absolutely essential for a successful classification result.

This thesis has demonstrated that GeOBIA needs not be conducted using expensive software or implementing complicated code. By combining different plugins in QGIS, an uncomplicated and effective GeOBIA workflow for detecting linear objects in a heterogeneous landscape was developed and found to be useful by a group of interpreters. Using FOSS applications for semi-automatic image analysis is essential to ensure transparency, reproducibility and accessibility of the research.

Currently, none of the FOSS GeOBIA applications have succeeded to be much of a competition to the proprietary software solutions on the market. It is the hope of the author that future research in the area of GeOBIA and FOSS will increase the awareness of the necessity to have alternatives to the proprietary and commercial solutions, and that in the very near future archaeologists can contribute to their development.

Abstract

Technical advances in the field of remote sensing have made it possible to create a large number of datasets with very high spectral, temporal or spatial resolution, however, in the field of archaeology, the evaluation of this data is still largely a manual undertaking. The issue with manual interpretation is that human interpreters are increasingly having difficulty coping with the sheer amount of data while in some cases, the human eye is not capable of processing the full range of information contained in these datasets. It is for this reason that (semi-)automatic classification workflows need to be developed in order to aid human interpreters in their image classification tasks.

This thesis is concerned with the development of a Geographic Object-Based Image Analysis Workflow for classifying LiDAR visualisations containing heterogeneous and linear objects. The study area that this workflow is applied to is the terraced landscape of the Lower Engadine, Switzerland, where the complex and steep terrain contains multiple agricultural terraces, irrigation/drainage ditches, roads and more.

The workflow makes use of only FOSS (Free and Open Source Software) applications in order to ensure full transparency, accessibility and reproducibility of the classification results. For this purpose, a number of FOSS and proprietary software was tested in order to determine the user friendliness, suitability and effectiveness of each of the options. Finally, it was decided to combine the SAGA GIS as well as the Orfeo Toolbox (OTB) plugins in QGIS.

In order to develop the final workflow, a number of studies regarding the suitability of different LiDAR visualisations as well as training data input options and smoothing filters were carried out. The final workflow makes use of an unfiltered slope visualisation, consists of six steps with an optional seventh step, and is capable of producing classification results that hold up against manual mapping results of the terrace edges that were used as a benchmark.

Finally, in order to assess whether the classification results generated by the workflow are useful to a human interpreter, a user study was carried out. 13 out of the 14 users stated that the classification results were helpful to them and because the workflow takes no longer than 5-10 minutes to carry out, it can be said that this workflow is capable of producing a useful classification of the study area with minimal time and effort.

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List of figures

Figure	Page number
Figure i: The Lower Engadine valley (marked with a red ellipse) is located in the far eastern part of the canton of Grisons (marked with a red rectangle). The present-day village of Ramosch is marked with a red dot. (Bundesamt für Landestopografie, 2019 and https://www.atlasderschweiz.ch/de (Institute of Cartography and Geoinformation, ETH Zurich)). Editing: Pierina Roffler.	10
Figure ii: The study area of this thesis, which can be split into an upper and a lower part. (Bundesamt für Landestopografie, 2019). Editing: Pierina Roffler.	11
Figure iii: The Lower Engadine Window with the outcrops of sedimentary Penninic rocks (green) and the metamorphic rocks of the Eastern Alpine Silvretta cristaline (brown) (Bundesamt für Landestopografie, 2020).	19
Figure iv: A view upstream the Inn River (western direction) with the village of Ramosch on the right hand side. The left side of the valley is composed of dolomite rock and is much more rugged than the right side which consists of Bündner schist. The right side also receives considerably more sunlight and is used for settlements and agriculture while the left side is largely forested (Jonas Blum).	20
Figure v: Terraces of type one which are still very distinctly visible in today's landscape. The Bronze and Iron Age settlement Ramosch Mottata was located on the prominent hill in the top right of the image (https://www.archaeologie.uzh.ch/de/prehist/forschung/Projekte/TERRA-(Terrassenlandschaft-Ramosch-Untereingadin).html [accessed 18.06.2020]).	23
Figure vi: Two terraces of type two are being examined by participants of the TERRA project. These terraces are much less distinct than the terraces of type one (Jonas Blum).	23
Figure vii: The hillside in the background contains numerous paths and irrigation ditches that are very difficult to differentiate (Jonas Blum).	24
Figure viii: Manual classification of a hillfort (top) compared to object-based methods (left) and pixel-based methods (right) (Sevara et al. 2016, 49).	27
Figure ix: The iterative segmentation and classification steps until the image objects correspond to the desired geo objects (Blaschke et al. 2014, 186).	31
Figure x: Schematic drawing of a pixel-based segmentation (Pierina Roffler).	32
Figure xi: Schematic drawing of a watershed segmentation (Pierina Roffler).	33
Figure xii: Schematic drawing of a region growing segmentation (Pierina Roffler).	34
Figure xiii: The relationships (hierarchical and neighbourhood) of different image objects at different scales (Blaschke et al. 2014, 187).	36

Figure xiv: The concept of semantics and hierarchies explained on the basis of a hillfort (Sevara and Pregesbauer 2014, 141).	37
Figure xv: Screenshot of the interface of Trimble eCognition during the selection of training segments.	43
Figure xvi: The GUI of ERDAS IMAGINE that resembles the GUI of Autodesk's AutoCAD (https://gisgeography.com/wp-content/uploads/2016/07/ERDAS-Imagine-Tokyo.png [accessed 17.06.2020]).	44
Figure xvii: Screenshot of the ERDAS IMAGINE GUI after region growing and merging the class signatures.	44
Figure xviii: Screenshot of the SAGA GUI after performing a supervised classification for grids on a Sky View Factor visualisation.	46
Figure xix: Screenshot of the SCP dock with the training input tab open, ready to enter Regions Of Interest (ROI) for different classes.	48
Figure xx: Screenshot of training polygons (green) that intersect multiple segments, leading to inaccurate classifications.	50
Figure xxi: A screenshot of the supervised classification tool in GRASS GIS after manually adding training polygons.	51
Figure xxii: Location of the lower testing terrace cluster (bottom left) and the upper testing area (above right) within an orthophoto (left) and a hillshade visualisation of the DTM (right) (Bundesamt für Landestopografie, 2019).	62
Figure xxiii: Classification with roads (left) leads to a more diffuse result than if only terrace flats and edges are classified (left). Roads: red, terrace flats: light green, terrace slopes: dark green.	63
Figure xxiv: Slope visualisations containing terraces, drainage/irrigation ditches and roads. As a reference, the image on the right shows the mapping results of Raba (1996) with the terrace edges in dark blue, the drainages in light blue and the roads shown in red (DTM: Bundesamt für Landestopografie (2019), visualisation created in RVT2.2.1 (Kokalj and Somrak 2019) by Pierina Roffler).	68
Figure xxv: The results of the Mean (left) and Gaussian (right) smoothing algorithms led to very blurred visualisations (DTM: Bundesamt für Landestopografie (2019), visualisation created in RVT2.2.1 (Kokalj and Somrak 2019) by Pierina Roffler).	70
Figure xxvi: The results of the Watershed (left) and Meanshift (right) segmentation. An apparent over segmentation in the Watershed segmentation is needed for exact training segments. One of the meanshift segments that spans multiple terrace flats and slopes is highlighted in yellow (DTM: Bundesamt für Landestopografie (2019), visualisation created in RVT2.2.1 (Kokalj and Somrak 2019) by Pierina Roffler).	71
Figure xxvii: Flowchart of the final workflow (Pierina Roffler).	76
Figure xxviii: The three steps of the graphical workflow modeller (Pierina Roffler).	77

<p>Figure xxix: The final classification result for a clipping of the upper study area. On the left hand side is the final classification in the format that an archaeologist would work with. For illustration purposes, the terrace edges that were mapped by Angelika Abderhalden-Raba were layered over the right image.</p>	78
<p>Figure xxx: The terrace type specific slope inclinations (yellow) and flat inclinations (red) for terrace type one (above) and two (middle) as well as the classification results of the lower study area. The mapping results of Raba (1996) are layered on top to serve as a benchmark.</p>	79
<p>Figure xxxi: The terrace type specific slope inclinations (yellow) and flat inclinations (red) for terrace type one (above) and two (middle) as well as the classification results of the lower study area. The mapping results of Raba (1996) are layered on top to serve as a benchmark.</p>	80
<p>Figure xxxii: The example terrace cluster that was given to the participant group without prior knowledge as hillshade (left) and classification (right). (DTM: Bundesamt für Landestopografie (2019), visualisation created in RVT2.2.1 (Kokalj and Somrak 2019) by Pierina Roffler).</p>	84
<p>Figure xxxiii: This test person stated that they would not address the flats and slopes in the classification as terraces, but once the mapping results are transferred from the hillshade onto the classification, the edges all lie on the border between the light green terrace flats and the dark green terrace slopes (DTM: Bundesamt für Landestopografie (2019), visualisation created in RVT2.2.1 (Kokalj and Somrak 2019) by Pierina Roffler).</p>	90
<p>Figure xxxiv: This participant stated that they had switched from using the classification to verify their results within the hillshade to using the hillshade to verify their results in the classification (DTM: Bundesamt für Landestopografie (2019), visualisation created in RVT2.2.1 (Kokalj and Somrak 2019) by Pierina Roffler).</p>	96

List of tables

Table	Page number
Table i: Summary of SwissALTI ^{3D} data sources and accuracies.	12
Table ii: Overview of the different terrace types (after Raba 1996, 88-89).	22
Table iii: Benefits and drawbacks of the tested software.	55
Table iv: Summary of the different LiDAR visualisations that were generated and used for testing purposes (after Kokalj and Hesse 2017).	57-58
Table v: Benefits and drawbacks of the Visualisations used by Nyffeler (Nyffeler 2018, 44). Original in German: translated by Pierina Roffler.	58-59
Table vi: Classification of different LiDAR visualisations of the same terrace cluster. Red: road, light green: terrace flat, dark green; terrace edge.	60-61
Table vii: Classification of different LiDAR visualisations of terraces and roads in the upper study area. Red: road, light green: terrace flat, dark green; terrace edge. Overlaid in blue are the terrace edges and in white the roads that were mapped by Angelika Abderhalden-Raba (Raba 1996).	64-66
Table viii: Classification of the terraces in the upper study area. In light green, potential terrace flats and in dark green potential terrace slopes are classified. The terrace edges that were mapped by Angelika Abderhalden-Raba are overlaid in blue (Raba 1996).	72-73
Table ix: The mapping results returned by members of group one (left). These results were compared to the edges that were mapped by Raba 1996 (right).	87-89
Table x: The mapping results returned by participants of group two (left). These results were compared to the edges that were mapped by Raba 1996 (right).	92-95

List of appendices

Appendix	Page number
Appendix i: Screenshot of the QGIS layer structure.	119
Appendix ii: Classification of the entire study area as the user would	120-121
Appendix iii: The specific inclinations of terrace flats (yellow) and terrace slopes (red) for terrace type one (above) and the same result with the terrace mapping results of Raba (1996) overlaid as a benchmark (below).	122-123
Appendix iv: The specific inclinations of terrace flats (yellow) and terrace slopes (red) for terrace type two (above) and the same result with the terrace mapping results of Raba (1996) overlaid as a benchmark (below).	124-125
Appendix v: The survey questionnaire (in English as well as in German) that was sent to two groups of participants in order to evaluate whether the classification that results from the developed workflow can be beneficial to a human interpreter.	126-127
Appendix vi: Answers to the questions on the survey questionnaire (appendix v).	128-130

Glossary

ALS: Airborne Laser Scanning

Anidif: Anisotropic Difference

DSM: Digital Surface Model

DTM: Digital Terrain Model

FOSS: Free and Open Source Software

(Ge)OBIA: (Geographic) Object-Based Image Analysis

GIS: Geographic Information System

GUI: Graphical User Interface

GRASS: Geographic Resources Analysis Support System

LiDAR: Light Detection and Ranging

LSMS: Large Scale Mean Shift

OTB: Orfeo Toolbox

ROI: Region Of Interest

SAGA: System for Automated Geoscientific Analysis

SCP: Semiautomatic Classification Plugin





SCRM: Size-Constrained Region Merging

SVM: Support Vector Machine

VRT: Virtual Raster Tile

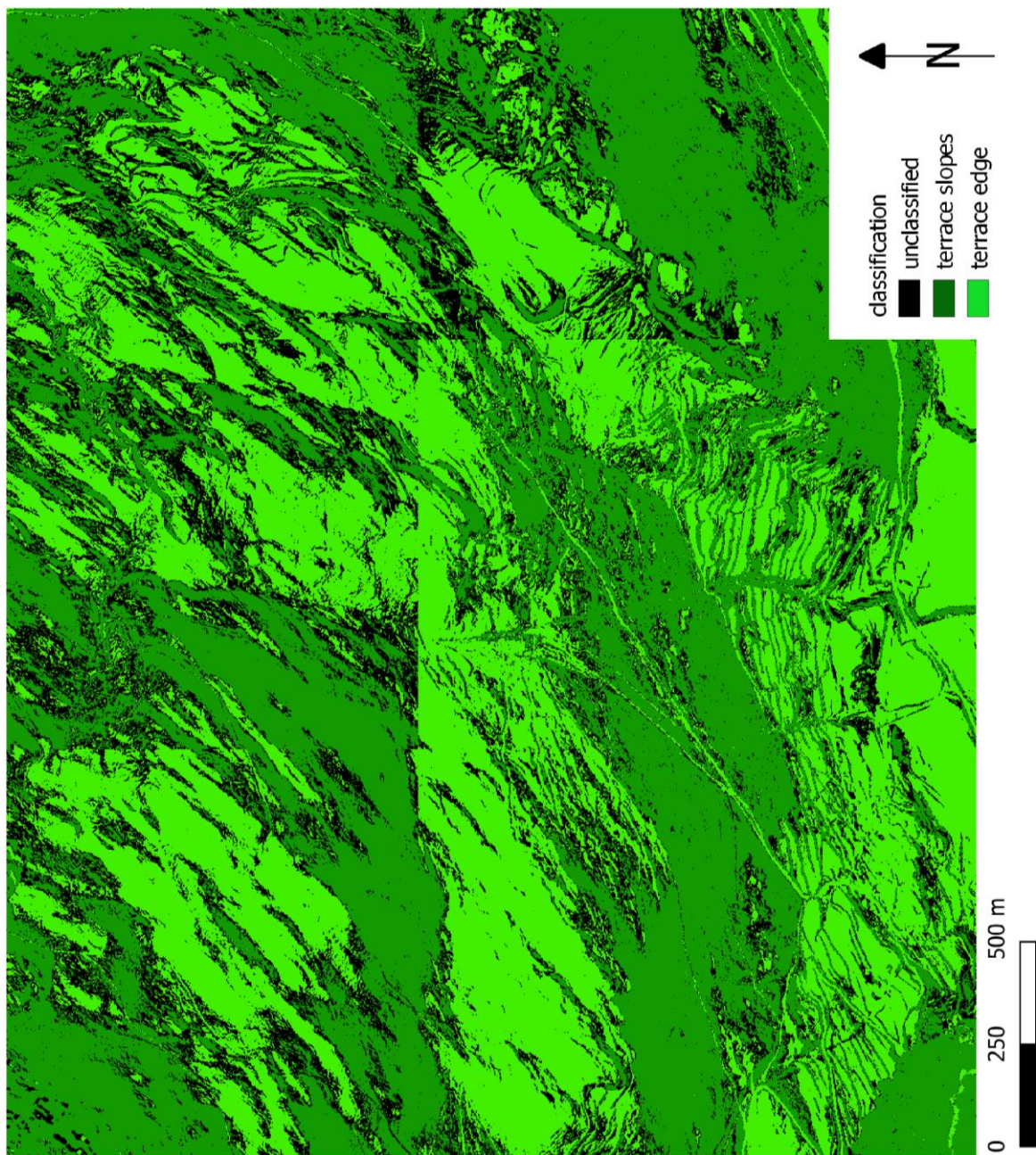
Appendix i

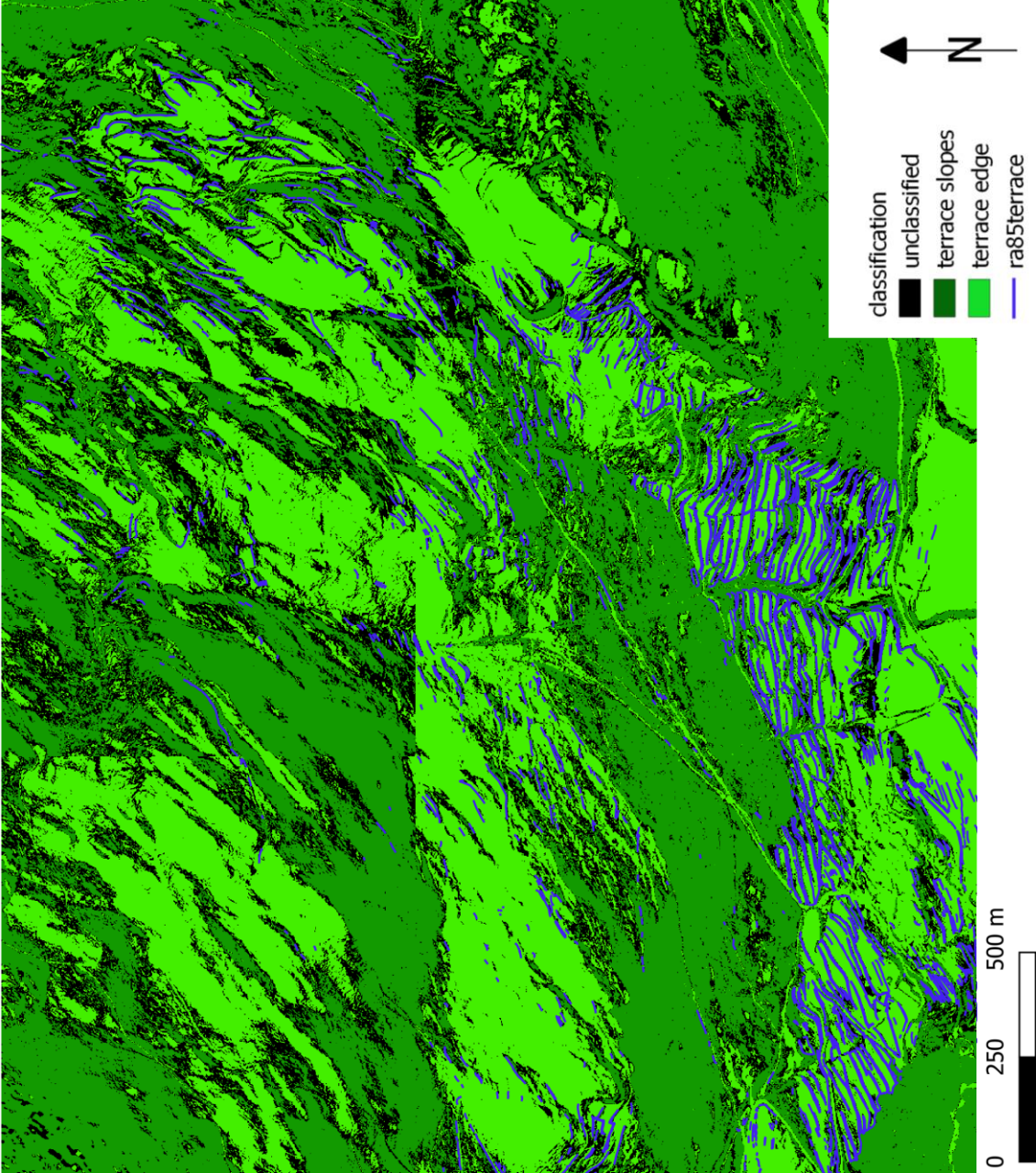
Screenshot of the QGIS layer structure.

- ▶  swiss_1199_2_SLOPE
- ▶  swiss_1199_2_HS_A315_H45
- ▶  benchmarks
 -  ra85drainage
 -  ra85paths_roads
 -  ra85terrace
- ▶  vector classes
 -  regular vectorised terrace flats
 -  regular vectorised terrace slopes
- ▶  terrace types
 - ▶  type 1
 -  type 1 slope
 -  type 1 flat
 - ▶  type 1 clipped
 - ▶  type 1
 - ▶  type 2
 -  type 2 flat
 -  type 2 slope
 - ▶  type 2 clipped
 - ▶  type 2
- ▶  regular
 -  segments regular meanshift
 - ▶  regular meanshift classification
 -  segments regular watershed
 - ▶  regular watershed classification
 - ▶  regular watershed classification no roads
 - ▶  Slope cropped
- ▶  anidif smoothing
 -  segments anidif meanshift
 - ▶  anidif meanshift classification
 - ▶  anidif meanshift classification no roads
 -  segments anidif watershed
 - ▶  anidif watershed classification
 - ▶  anidif watershed classification no roads
 - ▶  anidif smoothing
- ▶  lsms smoothing
 -  lsms meansift
 - ▶  lsms meansift classification
 -  lsms watershed
 - ▶  lsms watershed classification
 - ▶  lsms watershed classification no roads
 - ▶  lsms smoothing
- ▶  entire study area
 - ▶  tile 0
 - ▶  classification_tile0
 -  segmentation_tile0
 - ▶  tiles.0
 - ▶  tile1
 - ▶  classification_tile1
 -  segments_tile1
 - ▶  tiles.1
- ...
- ▶  tile 2
 - ▶  classification_tile2
 -  segments_tile2
 - ▶  tiles.2
- ▶  tile 3
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 -  segments_tile3
 - ▶  tiles.3
- ▶  tile 4
 - ▶  classification_tile4
 -  segments_tile4
 - ▶  tiles.4
- ▶  tile 5
 - ▶  classification_tile5
 -  segments_tile5
 - ▶  tiles.5
 - ▶  sub-group1
- ▶  tile 6
 - ▶  classification_tile6
 -  segments_6
 - ▶  tiles.6
- ▶  tile 7
 - ▶  classification_tile7
 -  segments_tile7
 - ▶  tiles.7
- ▶  tile 8
 - ▶  tiles.8
 - ▶  studyareaslope
- ▶  orthophotos
 -  1199-22
 -  1199-21
- ▶  lower study area
 - ▶  classification lower study area
 -  segments lower study area watershed
 - ▶  lower_study_area
- ▶  other smoothing filters
 - ▶  gaussian smoothing
 - ▶  mean smoothing

Appendix ii

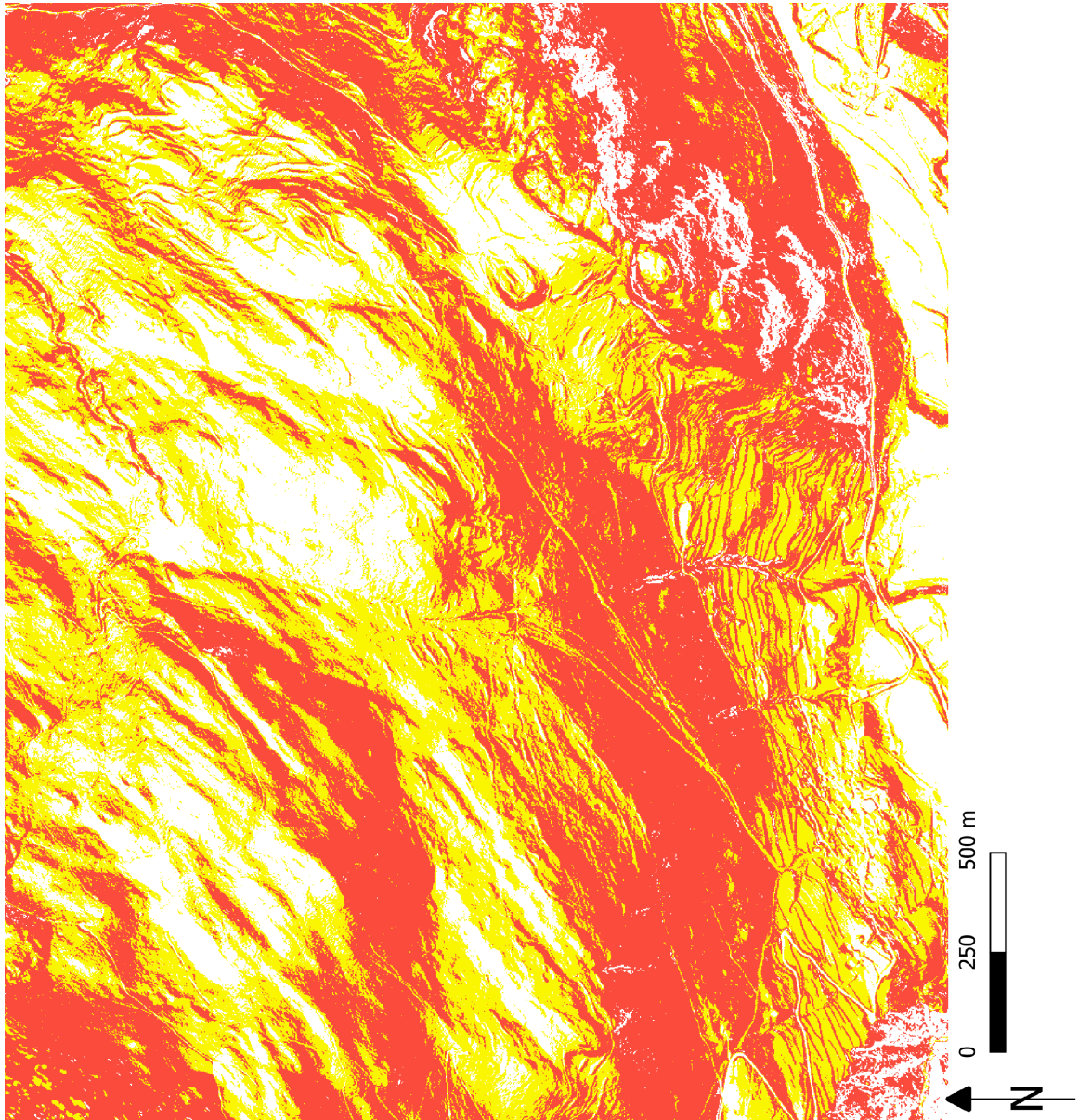
Classification of the entire study area (above) and the same classification with the terrace mapping results of Raba (1996) overlaid as a benchmark (below).

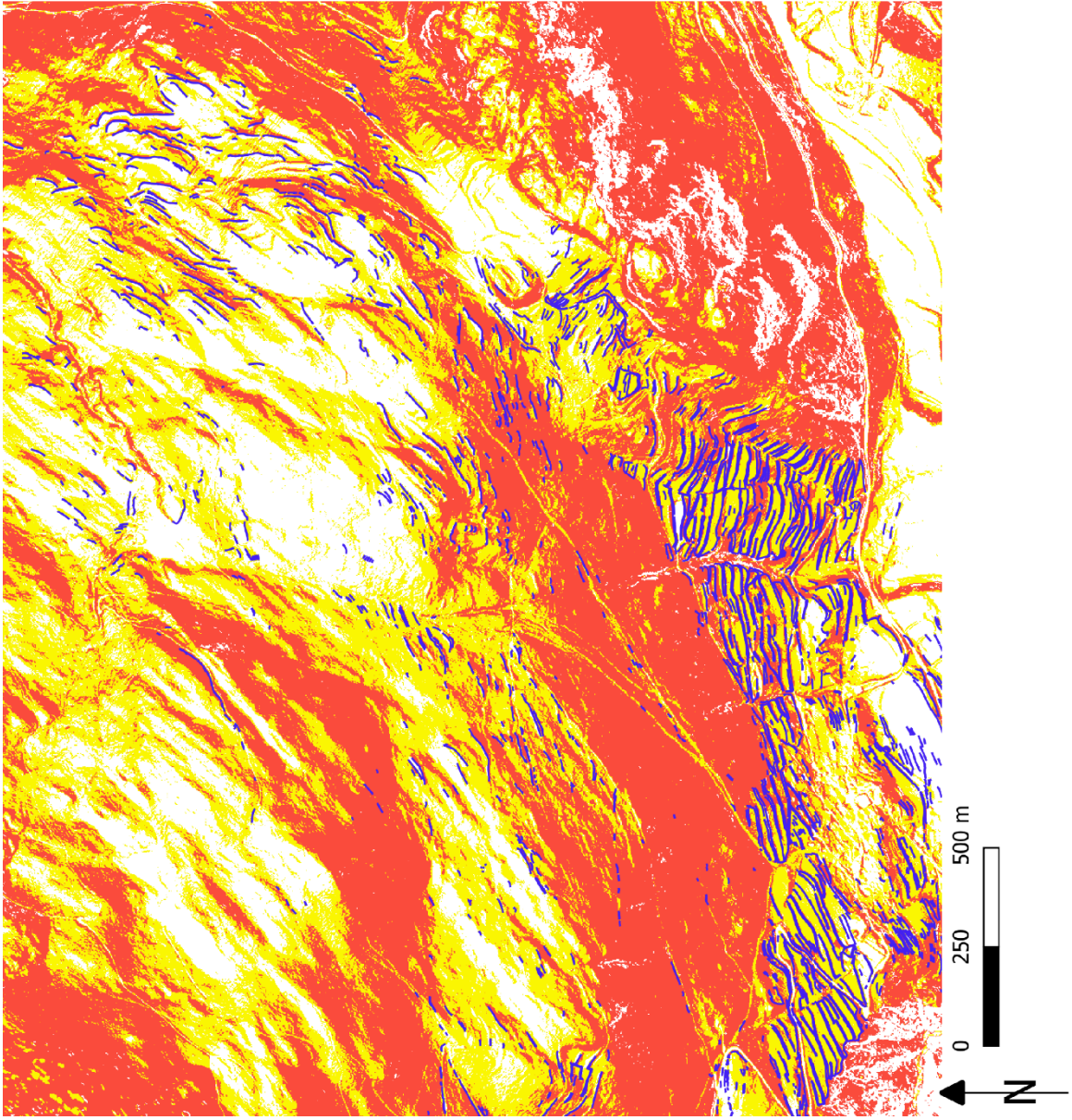




Appendix iii

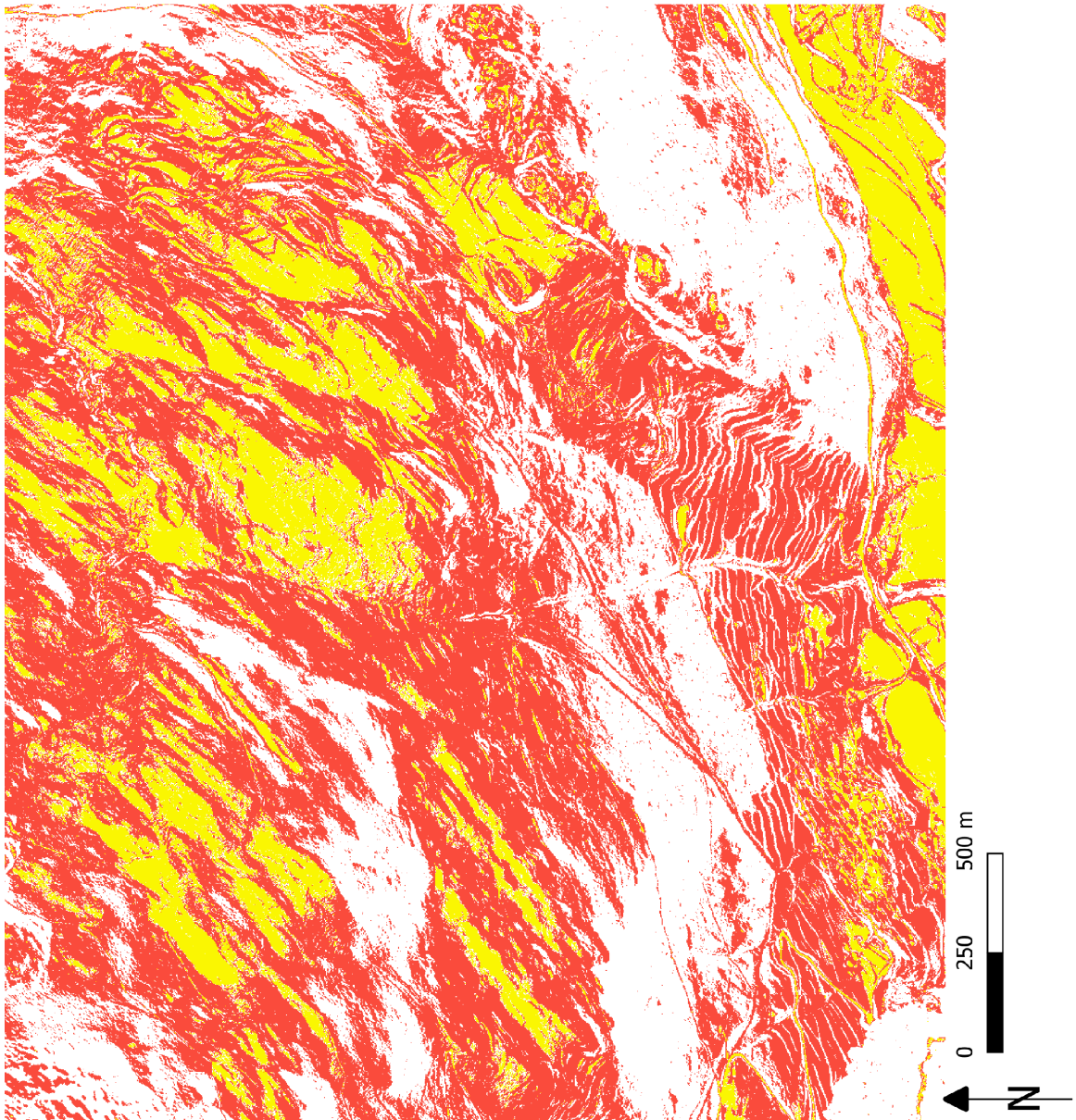
The specific inclinations of terrace flats (yellow) and terrace slopes (red) for terrace type one (above) and the same result with the terrace mapping results of Raba (1996) overlaid as a benchmark (below).

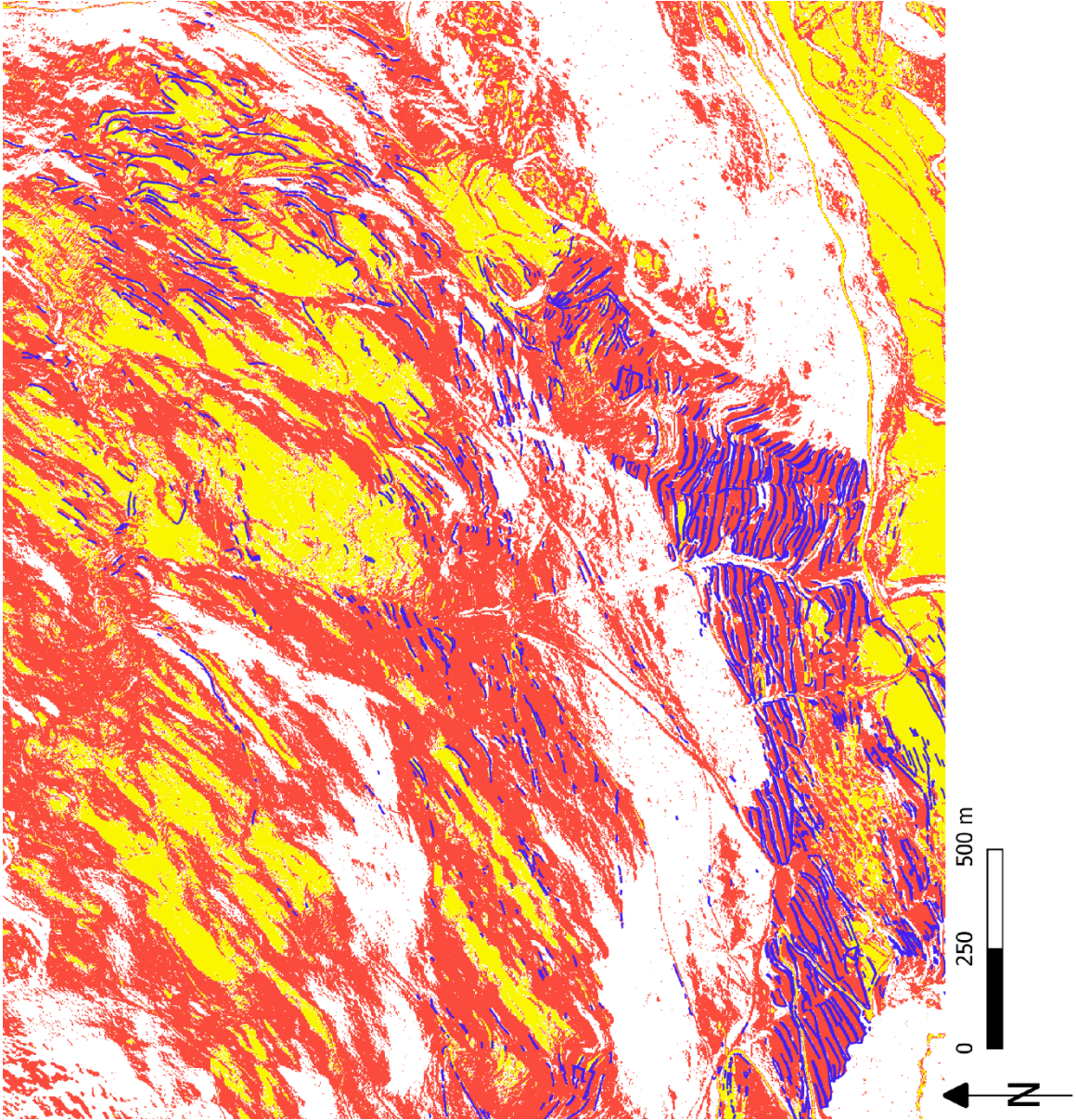




Appendix iv

The specific inclinations of terrace flats (yellow) and terrace slopes (red) for terrace type two (above) and the same result with the terrace mapping results of Raba (1996) overlaid as a benchmark (below).





Appendix v

The survey questionnaire (in English as well as in German) that was sent to two groups of participants in order to evaluate whether the classification that results from the developed workflow can be beneficial to a human interpreter.

Msc Archaeological Sciences: Digital Archaeology
Master Thesis 1084VTSY
Dr. Karsten Lambers

Pierina Roffler

03.05.2020

Survey

Dear test person

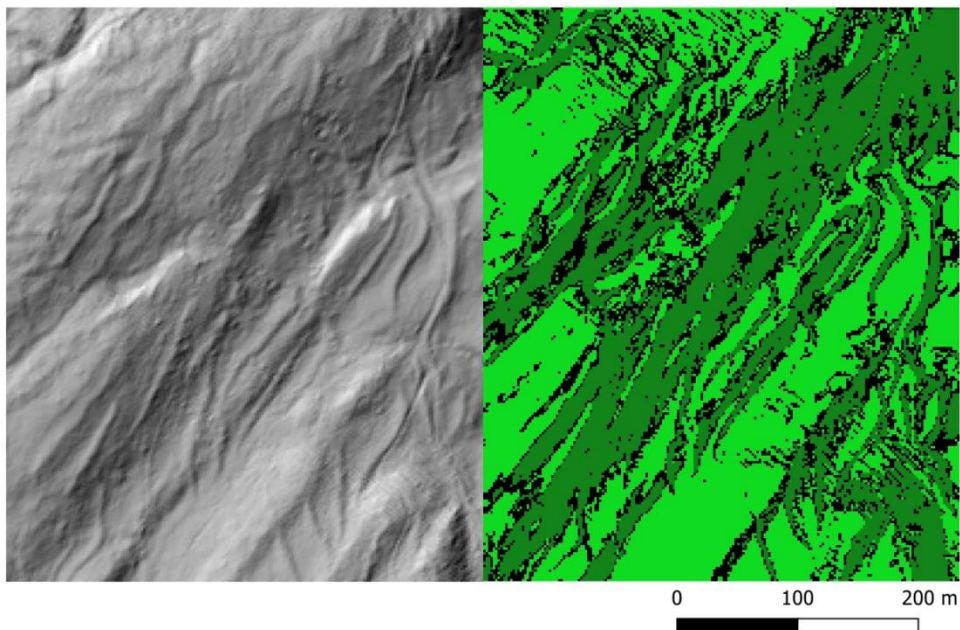
First of all, thank you for agreeing to take part in this survey! You have taken part in a field campaign of the TERRA project, you know the area and what an agricultural terrace looks like. The following two images both depict exactly the same area, the image on the left is a hillshade visualisation of the LiDAR DTM and the image on the right is a classification where light green marks potential terrace “flats” and dark green marks potential terrace “slopes”. Please use these images to mark the location of the terrace edges where and as you deem appropriate. You can open the images in a software of your choice or edit them directly on this page, and it does not matter whether you mark them on the hillshade or the classification. Please send your results back to me along with your answers to the following two questions:

- Did the classification help you with your decision on the location and extent of the terrace edges?
- Did you prefer working with the hillshade, the classification, or with the combination of both?

All answers will be used in anonymous form.

Thank you again for your participation and kind regards,

Pierina



Source: Digitales Terrainmodell der Amtlichen Vermessung (DTM-AV), Kanton Graubünden (2019).

Hinsichtlich der inhaltlichen Richtigkeit, Genauigkeit, Aktualität und Vollständigkeit der veröffentlichten Informationen wird keine Gewähr übernommen.

Umfrage

Liebe Probandin, Lieber Proband

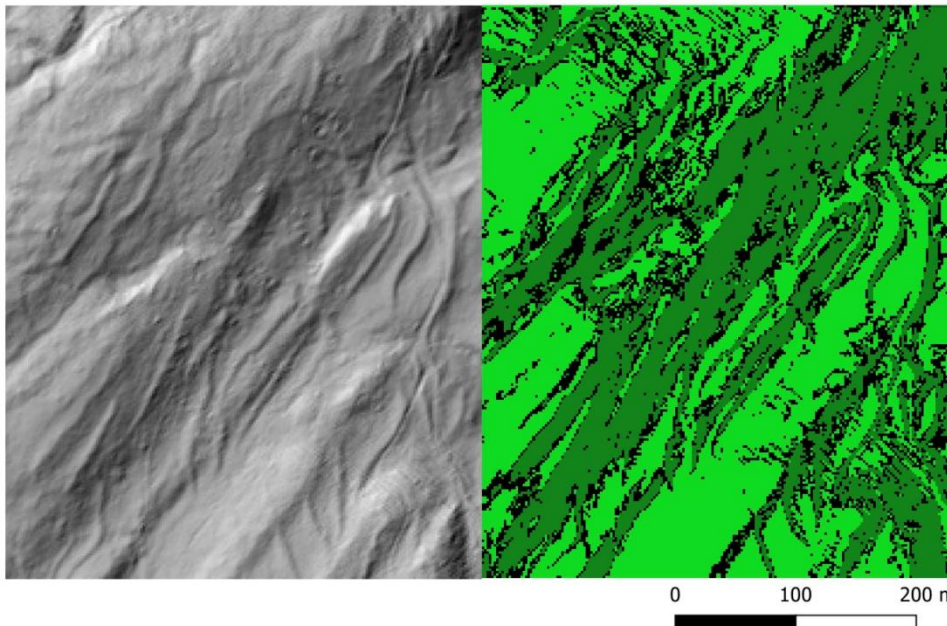
Vielen Dank für deine Teilnahme an dieser Umfrage! Du hast bereits an einer Feldkampagne des TERRA Projekts teilgenommen, du kennst das Forschungsgebiet und weisst, wie eine Ackerterrasse aussieht. Die folgenden zwei Bilder zeigen beide exakt denselben Ausschnitt, links ist eine Hillshade Visualisierung des LiDAR DTMs und rechts ist eine Klassifizierung, wobei potentielle Terrassenflächen in Hellgrün und potenzielle Terrassenhänge in Dunkelgrün markiert sind. Bitte verwende diese beiden Bilder um die Terrassenkanten dort wo du sie vermutest einzuzeichnen. Du kannst die Bilder entweder mit einer Software deiner Wahl oder direkt auf diesem Blatt bearbeiten, und es spielt dabei keine Rolle, ob du die Kanten auf dem Hillshade oder auf der Klassifizierung einzeichnest. Bitte sende mir deine Resultate zurück und beantworte zudem die folgenden zwei Fragen:

- Hat dir die Klassifizierung bei deiner Entscheidung über die Lage der Terrassenkanten geholfen?
- Hast du lieber mit dem Hillshade, mit der Klassifizierung oder mit einer Kombination von beiden Bildern gearbeitet?

Deine Resultate werden in anonymer Form verwendet.

Nochmals vielen Dank für deine Teilnahme und liebe Grüsse,

Pierina



Quelle: Digitales Terrainmodell der Amtlichen Vermessung (DTM-AV), Kanton Graubünden (2019).

Hinsichtlich der inhaltlichen Richtigkeit, Genauigkeit, Aktualität und Vollständigkeit der veröffentlichten Informationen wird keine Gewähr übernommen.

Appendix vi

Answers to the questions on the survey questionnaire (appendix v).

- 3) Did the classification help you with your decision on the location and extent of the terrace edges?
- 4) Did you prefer working with the hillshade, the classification, or with the combination of both?

<p>Group 1 In order to ensure complete anonymity, German answers were translated to English. The original statements can be requested from the author.</p>
<ol style="list-style-type: none"> 1) Rather not. Sometimes I was unsure when I consulted the classification, because I would not have referred to those areas that are classified as terrace flats or terrace slopes as a terrace. This probably has to do with my experience (see question 2). 2) I preferred working with the hillshade. This probably has to do with the fact that I am used to these types of visualisations and they appeal to me more than a mere colour-code. However, I noticed that in the upper area of the image I became a bit unsure... to me these objects look more like a landslide.
<ol style="list-style-type: none"> 1) Partly. The classification has an additional value when there are no clear edges visible in the LiDAR because of the composition of the ground. These types of diffuse areas are primarily located in the upper left corner (northwest?). Because the field survey showed that terraces are not horizontal and planar, but rather flattened terrain with slight unevenness, the classification conveyed the relationship between the objects in a clearer way. 2) The combination of both methods seems most profitable. The LiDAR is especially helpful for the orientation of the objects in the terrain.
<ol style="list-style-type: none"> 1) The classification helped me a lot because I could see the terrace edges well due to the change of colour (from dark green to light green). In this way I succeeded in finding terrace edges that were indistinct in the hillshade. 2) I used the hillshade to draw the terrace edges because the greyscale image seemed a better background than the colourful classification. Then I constantly compared the classification with the hillshade. I was under the impression that the classification enabled me to detect the starting and ending points of the terrace edges much more precisely.
<ol style="list-style-type: none"> 1) The classification helped me a little bit in deciding the location of the terrace edges, but was mostly used to confirm/substantiate the markings made in the hillshade figure. The classification was more useful in understanding the exact extent of the edges. The extent was slightly better visible in the classification once I knew what/where to look for. 2) I preferred using the combination of both, because in the hillshade map it was easier to recognize each terrace edge, whilst the classification map slightly better indicated the exact shape of each terrace edge. Only using the hillshade is suitable for identifying edges, but only using the classification is much more difficult as the differences between the hilly terrain and the terraces are the same color.

<p>1) I personally first looked at the classification, since you have mentioned in the introduction that the classification shows terrace edges and flats. This allowed for inclusion or exclusion of edges in some areas. I then used the hillshade for more precise definition of the edges, since it gave the impression of offering a higher level of detail/resolution. The classification did thus significantly help me in making my decisions.</p> <p>2) I preferred working with the combination of both, see the description of my methodology from the previous question. The fact that you have multiple sources of information, assuming that they are of good quality and relevant of course, always allows for the making of better decisions. I think that if you would incorporate both maps in a 3D GIS, which allows for a placement of the classification map on the three-dimensionally visualized LiDAR data, my decisions could have even been made with greater certainty.</p>
<p>1) Yes, the classification helps determine possible terraces and their extent. On the hillshade variant it is not clear when the terrace turns into a slope. In addition, it is also easier to determine from the classification that it is a flat area, which is a clearer indication of a terrace.</p> <p>2) I preferred to work with the classification for determining possible terraces, but I think it is important to work with multiple techniques because they will compliment each other, making the determination more reliable. Although it is also visible through the classification, the hillshade map gives a clear indication of the possible waterways that also played an important role.</p>
<p>1) Yes, the classification helped me.</p> <p>2) I worked with a combination.</p>

<p>Group 2</p> <p>In order to ensure complete anonymity, German answers were translated to English. The original statements can be requested from the author.</p>
<ol style="list-style-type: none"> 1) The classification helped if I was unsure about a line. 2) I think a combination is sensible, the hillshade for primary processing and then the classification for verification.
<ol style="list-style-type: none"> 1) The classification helped me verify my decisions. 2) With a combination of both → One can envision the terrace slopes better.
<ol style="list-style-type: none"> 1) Yes. It is easier to distinguish between two colours than to analyse greyscales. 2) I only used the classification.
<ol style="list-style-type: none"> 1) While some terraces are easily discernible on the hillshade visualisation, the classification reveals many more details. 2) I started off with the hillshade visualisation but quickly started to refer to the classification for plausibility checks. After only a few minutes I reversed the process without even realising it in the beginning. I discovered many more “steps” in the classification and compared them with the hillshade visualisation. In the process, I realised that in many instances, the hillshades are too vague, while the classification clearly indicated the presence of a terrace or step. Overall assessment: the classification greatly helped to get a much clearer picture of the topography.
<ol style="list-style-type: none"> 1) The classification helped. 2) I only used the classification.
<ol style="list-style-type: none"> 1) The classification helped. 2) Definitely a combination of both. First I only looked at the hillshade but after a while I realised that the classification makes things much clearer. The classification confirmed the hillshade.
<ol style="list-style-type: none"> 1) It made the marking easier. It shows more contrast. 2) Hillshade has less details and less contrast, one can identify things but in combination with the classification, the identification and marking is easier. Only the classification has very clear boundaries and details, which might make it easier for a layperson to discern.