Philipps Universität Marburg

# Detecting Alpine Treeline Ecotones – an Automated Remote Sensing Approach

Thesis Paper for the Project Seminar: Treelines of the World in SS 2020


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Abstract

# 1 Introduction

Alpine Treeline Ecotones (ATEs) are transitional zones between subalpine Forest and Alpine (tundra) ecotones (Holtmeier – Broll 2005, Winings 20013) also referred to as upper-treeline (Elliott 2017) and occur globally (Singh – Dharaiya – Mohapatra 2015, Bader – Llambí – Chase – Buckley – Toivonen – Camaerero – Cairn – Brown – Wiegand – Resler 2020). They span between the actual Timberline/Economic Forest Line though the Upper/Physiognomic-Biologic Forest Line and the tree species line which is adjoining the actual Alpine zone (Chhetri – Thai 2019, 1543). The position of the treeline is influenced by multiple factors at local and regional level, but temperature has been identified as the global driving factor (Körner 1998, Körner – Paulsen 2004, Holtmeier – Broll 2005, Bader 2007, Barredo – Mauri – Caudullo 2020). The global pattern can be described by spatial patterns in the x-y plane (discrete or diffuse, Figure 1) and by changes in tree stature (abrupt or gradual, Figure 2) in a multi-dimensional space (Harsch – Bader 2011, Bader – Llambí – Chase – Buckley – Toivonen – Camarero – Cairn – Brown – Wiegand – Resler 2020).

Although recognized, the distribution of ATE patterns have neither been mapped, nor been described yet, let alone explained. Earlier studies have identified abrupt, diffuse, island and krummholz spatial patterns of ATEs (Harsch – Hulme – McGlone – Duncan 2009, Harsch – Bader 2011, Figure 2). As seen, treelines dispaly a high variability and differ in multiple dimensions. A comparison of multiple studies suggest, that the different spatial patterns of ATEs reflect fundamental ecological controlling processes and that different ATEs react differently to climate change (Harsch – Bader 2011, Figure 1) Figure 3.

To better understand and categorize ATEs a standardized description and terminology of spatial patterns has been proposed on hillslope and landscape scale by Bader – Llambí – Chase – Buckley – Toivonen – Camarero – Cairn – Brown – Wiegand – Resler 2020, including hypotheses for the general mechanisms behind the patterns. The terminology and the multidimensional state-space can be most clearly understood from Figure 4.

After the definition and the characterization of the spatial patterns of ATEs, the following overview of ATE research shall serve as a basis for the workflow proposed in this methodological paper to globally detect ATEs.

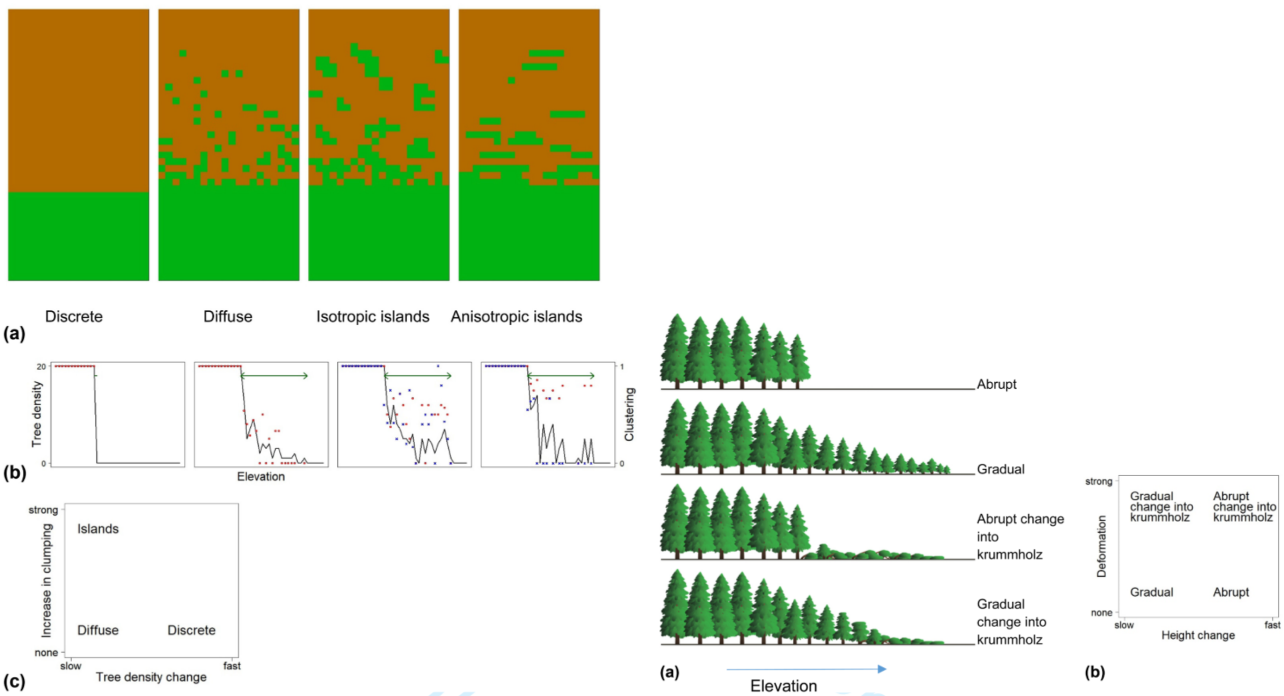


Figure 1: Left: Scheme of the spatial pattern of alpine treelines on the 2D x-y plane. a) Depicts the treeline as seen from above, while b) depicts the change of the treeline in the y direction (clustering of islands). c) Represents an abstraction of the pattern of treelines based on tree density change and the clustering of individual trees. Source: Bader – Llambí – Chase – Buckley – Toivonen – Camarero – Cairn – Brown – Wiegand – Resler 2020, Figure 1. Right: Scheme of (discrete) tree stature/height change responding to change in elevation. a) Vertical cross section. b) Abstraction of tree stature change based on height change and deformation of tree shape. Source: Bader – Llambí – Chase – Buckley – Toivonen – Camarero – Cairn – Brown – Wiegand – Resler 2020, Figure 2.

| | a) Rate of change | b) Type of change | Controlling processes (first-level) | Controlling processes (second- and third-level) |
|---|---|---|---|---|
| 2-D pattern | **Discrete** | | Mortality above but not in the ecotone | Any type of damage or stress. If gradual, growth limitation above the ecotone |
| | Ecotone | **Diffuse** | Mortality within the ecotone | Environmental heterogeneity or stochasticity. And/or ongoing seed-limited colonization |
| | | **Island** | Mortality within the ecotone | Positive feedback due to radiation damage, freezing damage, wind damage, snow redistribution (snow moulds, growing-season length), clustered seed dispersal, clonal reproduction |
| Tree stature | **Abrupt** | Into alpine | Mortality | Overheating, desiccation, photoinhibition, freezing damage, soil limitations |
| | | Into krummholz | Dieback | Winter desiccation, snow moulds, browsing, abrasion |
| | **Gradual** | No krummholz | Growth | Tissue formation (limited by a lack of heat) |
| | | Into krummholz | Growth and dieback | Tissue formation + winter desiccation, snow moulds, browsing, abrasion |

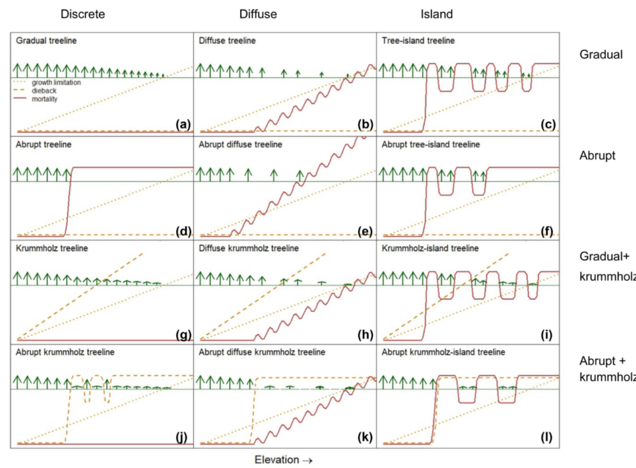


Figure 2: Left: Matrix of 2D spatial pattern, stature change and ecological processes which can contribute to the different types of ATEs. Source: Bader – Llambí – Chase – Buckley – Toivonen – Camarero – Cairn – Brown – Wiegand – Resler 2020, Table 1. Right: Matrix of the multidimensional state space of treeline forms depicting extreme cases of the different dimensions. Columns represent the spatial patterns in the x-y plane and rows the change in tree stature (size and shape). The lines represents the hypothesized first-level ecological processes behind the patterns along an elevational gradient. The dotted line displays the growth limitation, the dashed line the dieback and the continuous line the mortality. Growth limitation always occurs while dieback only affects if krummholz is involved. Source: Bader – Llambí – Chase – Buckley – Toivonen – Camarero – Cairn – Brown – Wiegand – Resler 2020, Figure 3.

# 2 Overview of Alpine Treeline Ecotone Research with focus on methodology

As already implied, Alpine Treeline Ecotone analysis has been carried out so far at local, regional and global scales with different focus. Chhetri – Thai 2019 investigate the use of GIS and remote sensing methods in ATE research between 1980 and 2017 and demonstrate that with the advances in sensor technology the access to higher resolution data and different data types the analysis methods diversify. Often it is hard to distinguish between the different methodological approaches because they all rely and depend on one-another and studies have usually applied multiple methods and methods have been applied for diverse scopes. The following overview of methods is crude and by no means comprehensive.

## 2.1 Statistical – analytical approach

Until the dispersal of openly available remote sensing products the approach was mainly concentrated on physiological/response based investigations with statistical analysis of local indicators based on in situ measurements. The main question was mainly: which environmental drivers control the location of ATE's and how complex are these (Körner 1998)? Drivers were differentiated on global, regional and local levels (Holtmeier – Broll 2005). As the main global driver temperature was defined (Körner 1998, Körner 2012, Holtmeier – Broll 2007, 2, Bonanomi – Rita – Allevato – Cesarano – Saulino – Di Pasquale – Allegrezza – Pesaresi – Borghetti – Rossi – Saracino 2018), but at regional and local levels it looks more diverse: topography (Brown 1994, Virtanen – Mikkola – Nikula – Christensen – Mazhitova – Oberman – Kuhry 2004, Bader – Ruijten 2008), geomorphologic processes, herbivory or anthropogenic disturbance (Chhetri – Thai 2019). Analysis of topographic actors with logistic regression was used frequently (e.g Brown 1994, Virtanen – Mikkola – Nikula – Christensen – Mazhitova – Oberman – Kuhry 2004, Bader – Ruijten 2008).

## 2.2 Remote sensing approach

The detection or localization of ATEs is facilitated by the availability of remote sensing data (satellite, airborne lately hyperspectral and UAV derived ortho/imagery). Specialized sensors operating in the R, G, B, IR, short-wave, hyperspectral and thermal regions of the electromagnetic spectrum give the possibility to approach and work with the specific spectral signatures (due to different absorption and reflection of radiation) of different vegetation entities. LiDAR data enables to include the factor height thus moving the analysis of treelines in a 3D space. The main focus of this methodological paper is on the remote sensing approach (automated detection) and exemplary papers are accentuated in a short summary. The use of GIS and remote sensing has been constantly increasing in treeline studies since 2000, with a few preceding pioneers. Earlier studies concentrated on mapping treeline positions and lately the interest shifted towards factors that control treeline variation (Chhetri – Thai 2019, 1543). It can also be seen that with the development of the respective sensors the interest and use moved to data with higher spatial resolution (LiDAR data, Hyperspectral data), which on the other hand attracts more cost and thus often thins out the studies due to the lack of monetary resources and also the use of proprietary software, which shows that there is a lot to do in means of open-source and reproducible best-practice applications and code. Usually there is little information on the software used. The use of remotely sensed data is usually combined with classical approaches like statistical analysis in complex research questions, from which the following main directions emerge:

### 2.2.1 *Mapping of ATEs*

To map ATEs, studies use aerial photographs and Landsat imagery to identify and quantify treelines (Brown 1994, Baker – Honaker – Weisberg 1995, Allen – Walsh 1996, Kimball – Weihrauch 2000, Virtanen – Mikkola – Nikula – Christensen – Mazhitova – Oberman – Kuhry 2004, Resler – Fonstad – Butler 2004) but often also vegetation indices are used Myneni – Keeling – Tucker 1997, Singh – Dharaiya – Mohapatra 2015, Mohapatra – Singh – Tripathi – Pandya 2019) to analyse treeline elevation (Allen – Walsh 1996, Kimball-Weihrauch 2000) and topographic variables/geomorphological parameters (slope, angle, curvature, relief) to explain treeline structure (patch-metrics) (Bryant et al 1991, Kimball-Weihrauch 2000). Tree population parameters are derived via PCA (e.g Baker – Weisberg 1997) and also species distribution modelling is a usual application (Chhetri – Shrestha – Cairns 2017).

### 2.2.2 *Montitoring ATEs/Change detection*

ATEs are space and time related phenomenons and they respond to changing environmental conditions, that is they can be sensitive to climate change (Singh – Dharaiya – Mohapatra 2015, Holtmeier – Broll 2005, Holtmeier – Broll 2007, Harsch – Bader 2011, Bader – Llambí – Chase – Buckley – Toivonen – Camarero – Cairn – Brown – Wiegand – Resler 2020). The rise in global average temperatures seems to lead to the geographically varying shifting of ecotones: on regional level to upward shift (Mohapatra – Singh – Tripathi – Pandya 2019) but also stable or retracting ATEs can be determined (Winnings 2013). It still has to be understood if the results are due data quality. The identification and quantification of change in the ATEs can be carried out with regional and global monitoring of ATEs (Chhetri – Thai 2019).

### 2.2.3 *Automated detection and mapping of ATEs*

Recently several research projects, Master theses and PhDs have investigated (semi-)automated detection and mapping methods of ATEs (see a list until 2013 in Winnings 2013 and the also the recent literature). The availability of high resolution data facilitate the use of more and more sophisticated methods. In this methodological paper we are concentrating specifically on automated analysis.

Automated methods imply the use of specific algorithms to extract information from remote sensing data, either pixel- or object based or recently also via Deep Learning (mainly CNNs). Some studies compare object- and pixel-based or different object-based segmentation methods (Immitzer – Atzberger – Koukal 2012, Winings 2013, Kupková – Červená – Suchá – Jakešová – Zagajewski – Březina – Albrechtová 2017). Also it has to be emphasized, that the automated detection of ATEs relies heavily on tree detection. Parallel to elaborated workflows for the automated detection of ATEs improvements are made continuously on tree detection methods and tree cover estimation (Whiteside – Esparon – Bartolo 2020) closely connected to the development of sensors and the new data processing methods (Qiu – Jing – Hu – Li – Tang 2020, Weinstein – Marconi – Bohlman – Zare – White 2019, Weinstein – Marconi – Bohlman – Zare – White 2020) and form an important basis for automated analysis. In the following the most prominent automated methods are presented shortly including a few case studies.

*Pixel-based* image analysis is working with the information encoded in pixels – it assigns each pixel to a specific class on the basis of the respective values of the spectral bands or index or morphometric information (slope, aspect, etc.). One drawback is, that the context of the pixels and it's neighbourhood gets neglected and the pixel values can be affected by circumstantial effects, like reflectance differences (Stueve – Isaacs – Tyrrell – Densmore 2011), shadow or clouds (Allen – Walsh 1996). Also it doesn't deal, with textures per se, and for this a textural analysis has to be done by using different filters (mean, sobel, focal, etc.).

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**Immitzer – Atzberger – Koukal 2012** used WW-2 satellite data (8 + 4 bands) for the identification of 10 tree species by means of Random forest classification (object-based vs. pixel-based) using spectra of a) manually delineated tree crowns b) derived tree crown polygons and reference samples for tree species.

**Winings 2013** used high resolution aerial imagery and LiDAR data in her Master's thesis to map the alpine treeline. She compared pixel- and object based classification. She used four different data input for both classification methods: NDVI, NDVI + multispectral aerial imagery, NDVI + tree height or NDVI + multispectral aerial imagery + tree height. In the case of the pixel-based classification the maximum likelihood and the unsupervised ISODATA (Iterative Self-Organizing Data Analysis Technique) clustering algorithms were compared. For the object-based image analysis multi-resolution segmentation was conducted, using colour and shape homogeneity. After the segmentation, the classes (tree vs. non-tree) were assigned based on object feature threshold. The accuracy for the pixel-based classifications was between 85.3 and 88.4 and for the object-based classification between 81.5 and 92.9 %, resulting in the best classification on the dataset with NDVI + multispectral aerial imagery + tree height. For the pixel-based image analysis ENVI and ERDAS and for the object-based analysis eCognition was used. **Kupková – Červená – Suchá – Jakešová – Zagajewski – Březina – Albrechtová 2017** used airborne hypersepctral (APEX and AISA DUAL) and Sentinel-A data for the classification of tundra vegetation by comparing pixel-based and object-based image analysis. Reference data was collected corresponding to 8 vegetation classes (anthropogenic areas, picea abies, pinus mugo dense, pinus mugo sparse, closed alpine grassland, grasses, alpine heathlands, wetlands and peat bogs; with a detailed and a simplified legend). Based on the difference in resolution the hyperspectral data and the Sattelite imagery was classified separately. Latter was only classified pixel-based and with SVM (Support Vector Machines with radial basis function), NN (Neural Net) and MLC (Maximum Likelihood Classification) algorithms. The hyperspectral data, having a higher spatial resolution was classified pixel- and object-based. For the pixel-based classification the SVM, NN and MLC algoriths were used. For the objcet-based classification Edge-based segmentation was used on the hyperspectral datasets. The hyperspectral data yielded better classification result thean the Satellite data, with SVM pixel-based classification. ENVI was used for the study.

*Object-based Image Analysis (GeOBIA)* on the other hand is dealing with the grouping of pixels in homogeneous groups, that is segments which bear similar spectral, spatial and textural information. From each segment additional information can be extracted (statistical information, size, shape and context). Different segmentation algorithms exist, which treat the image and the segments different.

**Middleton – Närhi – Sutinen – Sutinen 2008** used the Feature Extraction Module (Fx) implemented in ENVI to extract tree crowns from two aerial photographs (one from 1947 and one from 2003) via segmentation and feature classification with SVMwith textural, spatial and spectral information. The results were compared to forest inventory information and an upward shift was recorded on Lommoltunturi fell.

**Ranson – Montesano – Nelson 2011** used MODIS VCF (Vegetation Continuous Fields) tree cover data and segmentation to delineate the circumpolar taiga-tundra ecotone (TTE). The multi-annual VCF was adjusted usingf linear regressions and a vector layer was applied with previously delineated taiga and tundra biomes. Also the water bodies were masked out. Subsequently multi-resolution segmentation was carried out with eCongnition based on the homogeneity criterion. The resulting polygons were then classified on a specific range of adjusted VCF values which represent the TTE.

**Mishra – Mainali – Shrestha – Radenz – Karki 2018** used a UAV equipped with a Parrot Sequoia multispectral (Red, Green, Blue, Red Edge, Near Infra-Red) camera to acquire high resolution Imagery. Subsequently an SfM Orthoimage was calculated and then multi-resolution (based on the homogeneity criterium of scale, shape/colour and compactness/smoothness) and spectral difference segmentation (merging neighbouring objects based on a spectral threshold) was combined in eCognition to generate optimal feature space variables for the classes. Then the Random Forest Classifier was used for classification with 3 sets of features (spectral features; spectral features + geometric/shape features; spectral features + geometric/shape features + textural features) for species-level mapping of vegetation in the Himalayas.

**Whiteside – Esparon – Bartolo 2020** used derivatives of aerial imagery and WW2 satellite data (TGI, NDVI) resampled to 1 m filtered by a low-pass filter. Then a threshold-based multi-resolution segmentation was conducted with eCognition to assess the tree cover (in percentage) for each date (1964, 1976, 1981, 2010). The results were compared by date to assess the tree cover reduction (4%) during the 36 years.

**Luo – Dai 2020** used aerial imagery from 1962 and 1981, QuickBird Satellite image from 2006 was used as data input to map vegetation distribution after orthorectification, and generating a DEM. The land-cover types were delineated: Schrenkiana, Sabina and other. Multi-resolution (?) segmentation was conducted in eCognition subsequently combined with a k-nearest neighbour classification. The result was compared with fieldwork data collection (2010, 2011) of the two species. With the post-classification approach the land-cover change was examined between 1962, 1981 and 2006.

**Qiu – Jing – Hu – Li – Tang 2020** proposed a new spectral multi-scale (SMS) individual tree crown (ITC) delineation method using both brightness and spectra of high-resolution multrispectral imagery to be able to better delineate tree crowns in deciduous or mixed forests, where adjacent tree crowns are very close to each other. As the first step a morphological gradient map is calculated of multispectral images, then as a second step an inverse gradient image. Then initial treetops were extracted by multi-scale filtering and morphological operations with regard to tree crown shape which then were refined with the spectral reference of the neighbouring treecrowns (tree trops map). Subsequently the morphological gradient map is segmented by marker-controlled watershed segmentation which is then refined by the tree tops map, to receive an individual tree crown delineation map.

*Deep Learning* – contrary to pixel-based and GeOBIA – works on scene level and enables thus to deal better with the complex semantic structure of the increasing resolution of remote sensing images. A multitude of different Deep Learning models exist with different structures to fulfill different aims (e. g. segmentation, classification). The most common Deep Learning model structure are CNNs – Convolutzional Neural Networks, which are multi-layer networks with learning ability that consists of convolutional layers, pooling layers, and fully connected layers.

**Fricker – Ventura – Wolf – North – Davis – Franklin 2019** used airborne hyper-spectral imagery, LiDAR data and a CNN (Convolutional Neural Network) to automate tree species classification. 7 dominant tree species and a dead tree class were identified to serve as reference data for the CNN. A LiDAR derived CHM was used to digitize the individual tree canopies to prepare their pixels for the species labelling for the CNN. The classification was executed separately on the RGB and the hyper-spectral data. The classification with the hyper-spectral data (0.73 – 0.90) yielded better classification results than the RGB classification (0.41 – 0.88). All code and data to ensure reproducibility can be found online.

**Weinstein – Marconi – Bohlman – Zare – White 2019** proposed a semi-supervised CNN workflow based on the comparision of 3 unsupervised tree-crown segmentation algorithms. The result of the chosen tree crown segmentation (clustering of a CHM by tree height and crown width) of the LiDAR data was extracted as a bounding box from the RGB image, which dataset is then labeled self-supervised pretrained by a retinanet CNN. Then the CNN was retrained with a small hand-annotated dataset (supervised classificiation), to correct errors from the intitial un-supervised segmentation, which indeed improved the results of the prediction.

**Weinstein – Marconi – Bohlman – Zare – White 2020** build on the results from Weinstein – Marconi – Bohlman – Zare – White 2019 and tested if training datasets can be generalized and be used on completely different forested areas. Generally the performance of the model performance decreased, but when they were applied to spatially and spectrally similar forested areas the performance increased. Best was again, when the CNN was retrained by a handful of hand-annotated data from the same area.

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**Immitzer – Atzberger – Koukal 2012** used WW-2 satellite data (8 + 4 bands) for the identification of 10 tree species by means of Random forest classification (object-based vs. pixel-based) using spectra of a) manually delineated tree crowns b) derived tree crown polygons and reference samples for tree species.

**Winings 2013** used high resolution aerial imagery and LiDAR data in her Master's thesis to map the alpine treeline. She compared pixel- and object based classification. She used four different data input for both classification methods: NDVI, NDVI + multispectral aerial imagery, NDVI + tree height or NDVI + multispectral aerial imagery + tree height. In the case of the pixel-based classification the maximum likelihood and the unsupervised ISODATA (Iterative Self-Organizing Data Analysis Technique) clustering algorithms were compared. For the object-based image analysis multi-resolution segmentation was conducted, using colour and shape homogeneity. After the segmentation, the classes (tree vs. non-tree) were assigned based on object feature threshold. The accuracy for the pixel-based classifications was between 85.3 and 88.4 and for the object-based classification between 81.5 and 92.9 %, resulting in the best classification on the dataset with NDVI + multispectral aerial imagery + tree height. For the pixel-based image analysis ENVI and ERDAS and for the object-based analysis eCognition was used. **Kupková – Červená – Suchá – Jakešová – Zagajewski – Březina – Albrechtová 2017** used airborne hypersepctral (APEX and AISA DUAL) and Sentinel-A data for the classification of tundra vegetation by comparing pixel-based and object-based image analysis. Reference data was collected corresponding to 8 vegetation classes (anthropogenic areas, picea abies, pinus mugo dense, pinus mugo sparse, closed alpine grassland, grasses, alpine heathlands, wetlands and peat bogs; with a detailed and a simplified legend). Based on the difference in resolution the hyperspectral data and the Sattelite imagery was classified separately. Latter was only classified pixel-based and with SVM (Support Vector Machines with radial basis function), NN (Neural Net) and MLC (Maximum Likelihood Classification) algorithms. The hyperspectral data, having a higher spatial resolution was classified pixel- and object-based. For the pixel-based classification the SVM, NN and MLC algoriths were used. For the objcet-based classification Edge-based segmentation was used on the hyperspectral datasets. The hyperspectral data yielded better classification result thean the Satellite data, with SVM pixel-based classification. ENVI was used for the study.

*Object-based Image Analysis (GeOBIA)* on the other hand is dealing with the grouping of pixels in homogeneous groups, that is segments which bear similar spectral, spatial and textural information. From each segment additional information can be extracted (statistical information, size, shape and context). Different segmentation algorithms exist, which treat the image and the segments different.

**Middleton – Närhi – Sutinen – Sutinen 2008** used the Feature Extraction Module (Fx) implemented in ENVI to extract tree crowns from two aerial photographs (one from 1947 and one from 2003) via segmentation and feature classification with SVMwith textural, spatial and spectral information. The results were compared to forest inventory information and an upward shift was recorded on Lommoltunturi fell.

**Ranson – Montesano – Nelson 2011** used MODIS VCF (Vegetation Continuous Fields) tree cover data and segmentation to delineate the circumpolar taiga-tundra ecotone (TTE).

The multi-annual VCF was adjusted usingf linear regressions and a vector layer was applied with previously delineated taiga and tundra biomes. Also the water bodies were masked out. Subsequently multi-resolution segmentation was carried out with eCongnition based on the homogeneity criterion. The resulting polygons were then classified on a specific range of adjusted VCF values which represent the TTE.

**Mishra – Mainali – Shrestha – Radenz – Karki 2018** used a UAV equipped with a Parrot Sequoia multispectral (Red, Green, Blue, Red Edge, Near Infra-Red) camera to acquire high resolution Imagery. Subsequently an SfM Orthoimage was calculated and then multi-resolution (based on the homogeneity criterium of scale, shape/colour and compactness/smoothness) and spectral difference segmentation (merging neighbouring objects based on a spectral threshold) was combined in eCognition to generate optimal feature space variables for the classes. Then the Random Forest Classifier was used for classification with 3 sets of features (spectral features; spectral features + geometric/shape features; spectral features + geometric/shape features + textural features) for species-level mapping of vegetation in the Himalayas.

**Whiteside – Esparon – Bartolo 2020** used derivatives of aerial imagery and WW2 satellite data (TGI, NDVI) resampled to 1 m filtered by a low-pass filter. Then a threshold-based multi-resolution segmentation was conducted with eCognition to assess the tree cover (in percentage) for each date (1964, 1976, 1981, 2010). The results were compared by date to assess the tree cover reduction (4%) during the 36 years.

**Luo – Dai 2020** used aerial imagery from 1962 and 1981, QuickBird Satellite image from 2006 was used as data input to map vegetation distribution after orthorectification, and generating a DEM. The land-cover types were delineated: Schrenkiana, Sabina and other. Multi-resolution (?) segmentation was conducted in eCognition subsequently combined with a k-nearest neighbour classification. The result was compared with fieldwork data collection (2010, 2011) of the two species. With the post-classification approach the land-cover change was examined between 1962, 1981 and 2006.

**Qiu – Jing – Hu – Li – Tang 2020** proposed a new spectral multi-scale (SMS) individual tree crown (ITC) delineation method using both brightness and spectra of high-resolution multrispectral imagery to be able to better delineate tree crowns in deciduous or mixed forests, where adjacent tree crowns are very close to each other. As the first step a morphological gradient map is calculated of multispectral images, then as a second step an inverse gradient image. Then initial treetops were extracted by multi-scale filtering and morphological operations with regard to tree crown shape which then were refined with the spectral reference of the neighbouring treecrowns (tree trops map). Subsequently the morphological gradient map is segmented by marker-controlled watershed segmentation which is then refined by the tree tops map, to receive an individual tree crown delineation map.

*Deep Learning* – contrary to pixel-based and GeOBIA – works on scene level and enables thus to deal better with the complex semantic structure of the increasing resolution of remote sensing images. A multitude of different Deep Learning models exist with different structures to fulfill different aims (e. g. segmentation, classification). The most common Deep Learning model structure are CNNs – Convolutzional Neural Networks, which are multi-layer networks with learning ability that consists of convolutional layers, pooling layers, and fully connected layers.

**Fricker – Ventura – Wolf – North – Davis – Franklin 2019** used airborne hyper-spectral imagery, LiDAR data and a CNN (Convolutional Neural Network) to automate tree species classification. 7 dominant tree species and a dead tree class were identified to serve as reference data for the CNN. A LiDAR derived CHM was used to digitize the individual tree canopies to prepare their pixels for the species labelling for the CNN. The classification was executed separately on the RGB and the hyper-spectral data. The classification with the hyper-spectral data (0.73 – 0.90) yielded better classification results than the RGB classification (0.41 – 0.88). All code and data to ensure reproducibility can be found online.

**Weinstein – Marconi – Bohlman – Zare – White 2019** proposed a semi-supervised CNN workflow based on the comparision of 3 unsupervised tree-crown segmentation algorithms. The result of the chosen tree crown segmentation (clustering of a CHM by tree height and crown width) of the LiDAR data was extracted as a bounding box from the RGB image, which dataset is then labeled self-supervised pretrained by a retinanet CNN. Then the CNN was retrained with a small hand-annotated dataset (supervised classificiation), to correct errors from the intitial un-supervised segmentation, which indeed improved the results of the prediction.

**Weinstein – Marconi – Bohlman – Zare – White 2020** build on the results from Weinstein – Marconi – Bohlman – Zare – White 2019 and tested if training datasets can be generalized and be used on completely different forested areas. Generally the performance of the model performance decreased, but when they were applied to spatially and spectrally similar forested areas the performance increased. Best was again, when the CNN was retrained by a handful of hand-annotated data from the same area.