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„Classifying sparse vegetation in a proglacial valley using UAV imagery and Random Forest algorithm “

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Abstract	This investigation aimed to differentiate sparse vegetation in a steep alpine environment in the Austrian part of the Central Eastern Alps using remotely sensed data from an unmanned aerial vehicle (UAV) in combination with the Structure from Motion (SfM) technique and the Random Forest (RF) algorithm implemented in ArcGIS Pro. UAVs enable researchers to produce highly resolved data on a low budget with high flexibility. Our work contributes to the field of biogeomorphic research in proglacial areas as well as to the field of small-scale remote sensing and vegetation measuring. Our findings show that the occurrence of vegetation patches differs in terms of density and diversity within this relatively recent deglaciated environment. Highly resolved imagery from a consumer-grade UAV proved an appropriate basis for the SfM-based modeling of the research area as well as for vegetation mapping. Consideration must be paid to changing light conditions during data acquisition, especially with multispectral sensors. The RF-implementation in ArcGIS Pro provided satisfactory results in this use case with the target class discrimination based on the RGB orthomosaic and the DEM as supplementary datasets.
Keywords	UAV remote sensing; Random Forest; vegetation mapping; proglacial; Structure from Motion
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Abstract

This investigation aimed to differentiate sparse vegetation in a steep alpine environment in the Austrian part of the Central Eastern Alps using remotely sensed data from an unmanned aerial vehicle (UAV) in combination with the *Structure from Motion* (SfM) technique and the *Random Forest* (RF) algorithm implemented in *ArcGIS Pro*. UAVs enable researchers to produce highly re-solved data on a low budget with high flexibility. Our work contributes to the field of bio-geo-morphic research in proglacial areas as well as to the field of small-scale remote sensing and vegetation measuring. Our findings show that the occurrence of vegetation patches differs in terms of density and diversity within this relatively recent deglaciated environment. Highly re-solved imagery from a consumer-grade UAV proved an appropriate basis for the SfM-based mod-eling of the research area as well as for vegetation mapping. Consideration must be paid to changing light conditions during data acquisition, especially with multispectral sensors. The RF-implementation in ArcGIS Pro provided satisfactory results in this use case with the target class discrimination based on the RGB orthomosaic and the DEM as supplementary datasets.

Kurzfassung

In dieser Arbeit wurden die Detektion und Klassifizierung von spärlich vorhandener Vegetation in einem hochalpinen Teil der österreichischen Ostalpen vorgenommen. Dies wurde mithilfe von Fernerkundungsdaten durchgeführt, welche von einem unbemannten Luftfahrzeug (Drohne) aufgenommen wurden und in weiterer Folge mithilfe des *Structure from Motion* (SfM) Verfah-rens und des *Random Forest* Algorithmus in *ArcGIS Pro* modelliert und analysiert wurden. Unbe-mannte Luftfahrzeuge ermöglichen es Forscher:innen hochauflösende Geodaten kostengünstig und flexibel zu generieren. Diese Arbeit leistet einen Beitrag zur biogeomorphologischen For-schung in proglazialen Gebieten sowie zum Feld der kleinskaligen Fernerkundung und Vegetati-onsmessung. Unsere Ergebnisse zeigen ein ungleichmäßiges Auftreten von Bewuchsflächen in dieser erst kürzlich eisfrei gewordenen Umgebung hinsichtlich Bewuchsdichte und Verteilung. Die hochauflösenden Aufnahmen des unbemannten Luftfahrzeugs erwiesen sich als geeignete Grundlage für eine SfM-basierte 3D-Modellierung des Untersuchungsgebiets sowie für die da-rauffolgende Vegetationskartierung. Bei der Datenaufnahme muss besonderes Augenmerk auf die herrschenden Lichtbedingungen gelegt werden, speziell beim Einsatz von multispektralen Sensoren, welche darauf besonders sensibel reagieren. In unserem Anwendungsfall lieferte der

in ArcGIS Pro implementierte Random Forest Algorithmus zufriedenstellende Resultate in Bezug auf die Vegetationsklassifikation. Die Klassifikation wurde auf Basis des RGB-Orthomosaiks durchgeführt, mit dem digitalen Geländemodell als zusätzliche Informationsebene.

Introduction

Erosion processes, such as landslides, debris flows or rockfalls, constitute a permanent threat for human settlements and infrastructure in high mountain environments (Miklau et al. 2009). This is especially true for regions like the study area of this work because glaciated basins have much higher erosion rates than non-glaciated basins. Even though it is difficult to distinguish the relative amount of glacial and non-glacial erosion in the same area, this hypothesis showed to be true as different research activities proved (Hinderer et al. 2013, Lane et al. 2016). This fact might lead to the assumption that erosion processes are slowed down with the ongoing climate change as the melting of glaciers turns glacial basins into non-glacial basins. The period in which this transition takes place however, is characterized by heavy reworking of sediments that were conditioned by glaciers beforehand which is referred to as paraglacial adjustment which was firstly described by Church & Ryder (1972) and later by Ballantyne (2002). The timespan in which this reshaping takes place is the so-called paraglacial period. The length of the paraglacial period cannot be defined exactly, as different parts of the system adapt to changes with various rapidity and besides that, the whole procedure varies strongly among different landscapes and spatial scales (Ballantyne 2002).

The retreat of a glacier changes destabilizes geomorphological systems in multiple ways. Areas that used to be covered with ice are being exposed, which destabilizes slopes and makes more sediment accessible for fluvial and gravitational erosion. For instance, as steep hillsides, which had been formed by the glacier before are being debuttressed by the glacier's decline events like landslides are favored (Porter at al. 2010) which leads to a bigger sediment input into proglacial streams. Eroded material which is carried by proglacial streams is transported much faster than it would be on the surface of a glacier which results in a much larger sediment yield in downstream basins (Uhlmann et al. 2013).

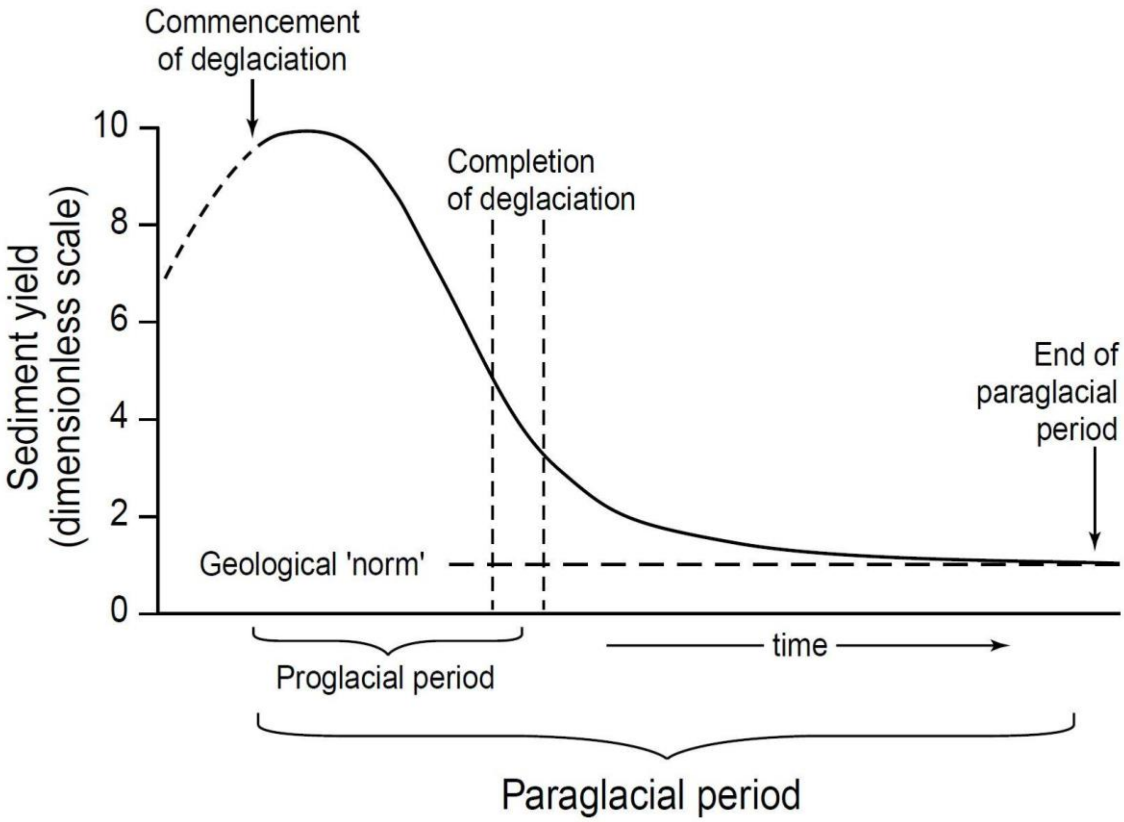

Figure 1: Change of sediment yield in the paraglacial period (Ballantyne 2002).

These incidents confront inhabitants, researchers and other stakeholders with great challenges. The study area of this work, the Kaunertal valley, is situated in a high alpine environment and is directly affected by previously mentioned circumstances. Local residents are mostly concerned about the apparent events such as landslides and rockfalls which pose a direct threat for human beings and their infrastructure. Effects for other parties however, such as the operator of the hydroelectric power plant TIWAG, are not this obvious but not less severe. High sedimentation in the downstream reservoir leads too much higher expenses than estimated beforehand caused by reparation costs and the more often needed dredging of the basin (TIWAG 2017, zek Hydro 2017, Tiroler Tageszeitung 2017).

Vegetation cover can counteract the instability of affected slopes and reduce the amount of eroded material (Scheurer et al. 2009), hence the establishment of vegetation cover is of great interest for local stakeholders. In the last four decades a majority of alpine areas have experi-enced an increase in plant productivity. However, it is unlikely that this trend is strong enough to counteract the negative consequences of global warming (Rumpf et al. 2022). For plant species it is difficult to settle in an environment that is affected by constant geomorphological activity. Provided that these disturbances are followed by a sufficiently long timespan without major geomorphological activity and that other site conditions like wind, temperature, solar radiation and exposition are favorable, succession may take place (Matthews & Whittaker 1987, Matthews 1992, Körner 1995). Succession describes the change of species composition in a specific order following some kind of disturbance (Matthews 1992). Looking at an area that is completely uninhabited following a major disturbance (like the retreat of the glacier in our study area), primary succession begins from zero several years after the glacier retreat. The geoecological succession model, which includes biological and physical factors (Matthews 1992), is most appropriate for the setting of this research as it not only relies on biological factors but honors the strong abiotic influence caused by geomorphologic activities. The multistage succession procedure starts with the establishment of pioneer species which are able to reach remote locations like proglacial areas because their spores are mostly transported by wind (Erschbamer et al. 2008, Nagl & Erschbamer 2008). In the following years, different species try to settle and the local ecosystem becomes denser and more diverse. The earlier this colonization occurs the better erosion can be counteracted. Geoecological succession, however, is not a simple one-way sequence of development stages and successional pathways are not always this straight (Matthews 1992). Increasing vegetation cover goes along with the development of soils and if enough sediment is stabilized the intensity of geomorphological activities decreases (Ballantyne 2002), although disturbances may still occur and hamper the progress of the successional development. As succession advances, the importance of biotic factors increases, while the influence of abiotic factors decreases (Matthews 1992).

Speeding up the establishment of vegetation cover without technical interventions is one of the ideas behind nature-based solutions (NBS), which are the subject of research and development in the Innovation Action project PHUSICOS, funded by the EU Horizon 2020 program (https://phusicos.eu/). Nature-based solutions are meant to be energy- and resource-efficient while bringing socioeconomic benefits by helping communities to address challenges in sustainable ways (European Commission 2015). In the context of this project the goal is to find endemic plants, which are already successful at stabilizing slopes due to their bigger leaves and/or denser root systems. These species should be reproduced and their functionalities supported with microbes. This should not only reduce erosion processes but also increase biodiversity. The upscaling of fundamental biogeomorphical research is facilitated by high resolution vegetation data of study areas.

Key research questions here are:

1. What are the limitations of commercially available UAVs and low-cost multi-spectral cameras in the context of vegetation remote sensing in proglacial areas?
2. How is vegetation dispersed in the study area with regard to density and diversity?
3. Is the implemented Random Forest algorithm in ArcGIS Pro an appropriate approach for classifying sparse vegetation based on RGB imagery?

Robust approaches for vegetation estimation using satellite data like Sentinel or Landsat in combination with vegetation indices have been developed in recent years (Jönsson et al. 2018, Zeng et al. 2022) and especially the Sentinel series is still widely used for scientific research (Guerini et al. 2020). But even with state-of-the-art sensor technology, there remains the problem of the insufficient spatial resolution of satellite-based data for various applications, such as the detection and discrimination of small plants. Studies using high-resolution imagery from the *QuickBird* satellite showed a significant correlation between spectral variability in QuickBird images and species richness, whereas this effect was not observable in lower resolved imagery (Rocchini 2007). This emphasizes the need of highly resolved data in order to successfully perform small-scale vegetation mapping. Airborne systems carried by planes are able to provide data with a higher spatial resolution but are mostly connected with costs, a low number of spectral bands and long revisiting periods, which makes them less attractive for our use case.

Unmanned aerial systems have experienced a massive upswing in usage in the last decade and are partially able to close the gap between the fast-but-coarse satellite sensing technologies and time-intensive data collection directly in the field. Today we are fully involved in a new era of remote sensing with consumer-grade UAVs being affordable for every research institution and growing sensor capabilities for this kind of platform. Unmanned aerial systems seem to combine the benefits of conventional methods like spaceborne and airborne remote sensing with their high spatial and spectral resolution - if equipped with appropriate sensors - and short revisiting intervals. The constraint of limited battery capacities of UAVs narrows the potential applications but is also widened constantly by the fast developments in this sector. Enterprise-segment unmanned aerial systems achieve much higher flight times than the model we used and are getting cheaper every year (DJI 2022). In conventional remote sensing approaches, the collection of field observations for training- and reference-data was a time-consuming process which was also connected with further obstacles such as geolocation inaccuracies and biases. In very high resolution (VHR-)datasets, samples are extracted directly from the images since the visual identification of the target classes is possible in highly resolved imagery (Kattenborn et al. 2019a). Using unmanned aerial vehicles (UAV), data for vegetation classification has several advantages, such as the provision of three-dimensional information through the Structure from Motion technology (SfM) as well as the use of low-cost multispectral sensors (Feng et al. 2015, Sadeghi & Sohrabi 2018, Nagendra et al. 2013, Nijland et al. 2015, Kattenborn et al. 2019b).

Materials and Methods

Study area

The *Kaunertal* valley is located in western Austria (federal state Tyrol) and is situated in the *Ötztaler Alps*, which are part of the crystalline Central Eastern Alps. The *Gepatschferner* glacier at the southern end of the valley is the second largest glacier in Austria. The study area is a hanging side-valley northeast of the retreating Gepatschferner glacier tongue and comprises roughly 1.75 km^2 in size. Altitudes range from 2300 to 2900 meters above sea level. The bedrock consists of more than 70 % paragneiss, in combination with orthogneisses and amphibolites (Hammer 1923, Vehling 2016). The present climate is characterized by a relatively low amount of precipitation and low temperatures throughout the whole year, classifying the Kaunertal as an inner-alpine dry valley (Vehling 2016, Efthymiadis et al. 2007). The climatic conditions are strongly influenced by the valley's situation on the north side of the Alps main ridge which shields the Kaunertal from weather fronts. Measurements from the *Weißsee* weather station at 2540 meters (which is the closest to the research area) show an average precipitation of 1150 mm per year. The mean temperature is -0.4 degrees Celsius and during winter values below -10 degrees are common (Vehling 2016). Due to highly variable landscape traits such as exposure and wind conditions these values can vary strongly within small areas.

The once glaciated catchment shows a distinctive U Shape with lateral, middle and end moraine features, as well as various roche moutonnées along the perennial river, which in parts is a braided river system of Strahler stream order one. The study area drains through the stream *Fagge* which is fed by several smaller creeks and the glacier itself. On its way to the *Inn* and hereinafter into the *Danube* the Fagge crosses a six kilometers long reservoir which is located in the middle part of the valley. Glacial dynamics have a strong influence on the drainage behavior wherefore the maximum run off is reached during summer when great amounts of melt water are added to the stream and rainfall reaches its peak. Measurements performed by Tschada & Hofer (1990) over a time range of 25 years show that through fluvial sediment transport a load of more than 58000 m^3 of solids and bedload is washed out of the upper valley into the reservoir each year.

The steep alpine slopes and the relatively young (< 170 years) deglaciated unconsolidated moraine sediments are prerequisites for high geomorphological activity. Rockfalls, debris flows and some landslides can be observed throughout the study area (Vehling 2016). The research area is only sparsely vegetated. Due to the lack of sunshine, long-lasting snow cover and high geomorphologic activity, the highest growing plants are *Juniperus* and *Salixes* with a maximum height of 50 centimeters. Different terrain ages can be observed along the area of glacier retreat, interrupted by patches of geomorphic activity or stability (see Figure 2). The area in the south-west has been ice-free for roughly 50 years so an intermediate successional stage would be expected here (Matthews 1992). Bordering it on the lower side, areas of higher terrain age are located which have been ice-free for approximately 100 years and fall into the late successional stage (Matthews 1992). The former extent of the Little Ice Age (≈ 170 years ago) is clearly visible below in the form of distinct moraines.

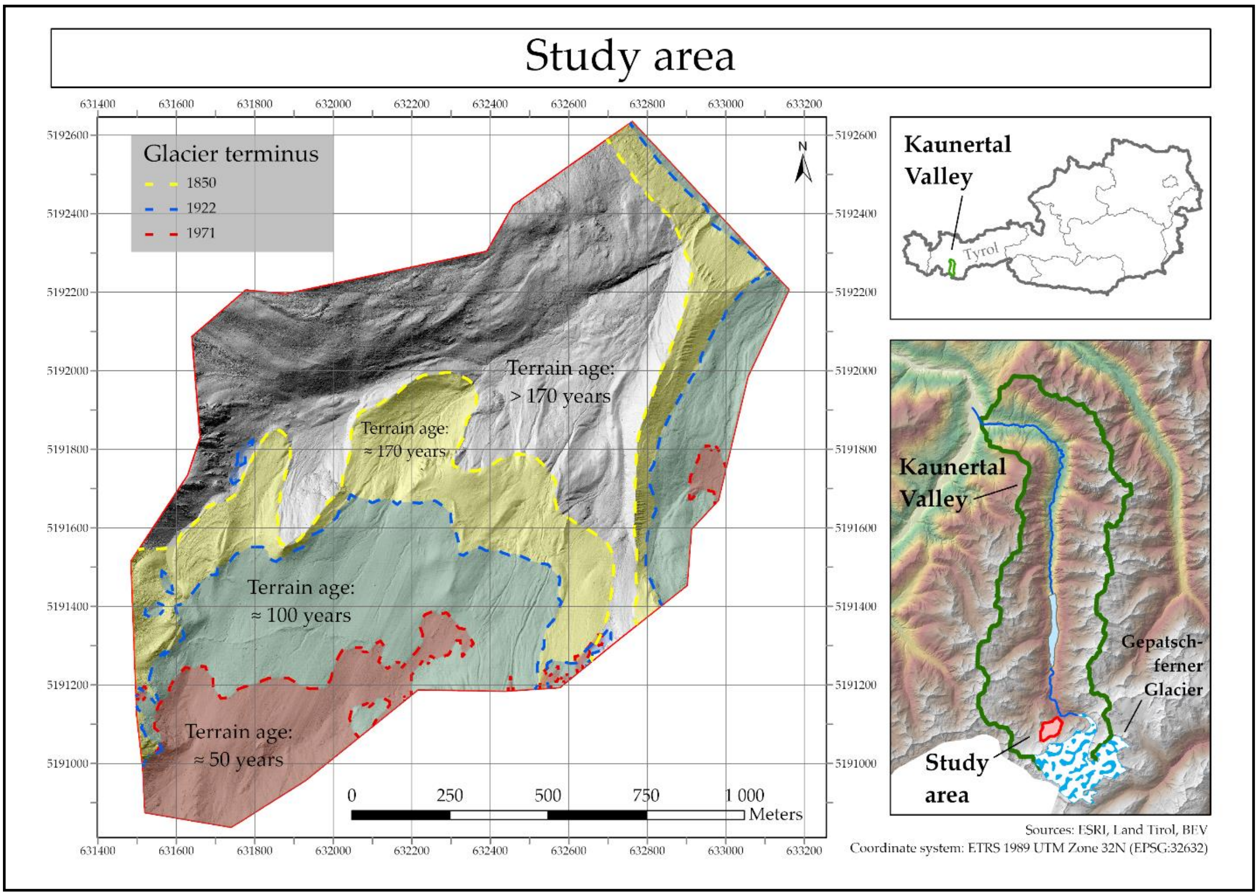

Figure 2: Study area. Overview and detailed map of the study area with glacier terminus lines and terrain ages. The study area is located in the federal state of Tyrol in Austria. (Zangerl 2022).

Data collection

The data collection took place at the beginning of August 2019 over the course of three days. The first step was the arrangement and GNSS measurement of 39 GCPs (ground control points) in the study area, some of which were sprayed on rocks and some fixed on the ground as laminated A3-printouts. The GCPs were located using a *Trimble Zephyr 3* differential GNSS receiver. A *DJI Phantom 4 Pro V2.0* equipped with a 1-inch 20-megapixel *CMOS* sensor and a focal length of 8.8 mm / 24 mm (35 mm equivalent) (DJI 2021) and two mounted multispectral cameras from *MAPIR* (https://www.mapir.camera/) was used to obtain high resolution imagery of the research area. One camera captures images in the red edge channel (725 nm) which acts as an indicator for plant productivity by measuring the chlorophyll content in leaves (Curran et al. 1990, EUMeTrain 2010). The second camera employs a combination of three spectral bands (orange: 490 nm, cyan: 615 nm, near infrared: 808 nm) which were used to measure sparse vegetation on bare soil or in between rocks (MAPIR 2021a). Both cameras use a 12-megapixel *Sony Exmor R IMX117* sensor with a focal length of 19 mm and produce images with 4000 x 3000 pixels (MAPIR 2021b). These cameras were originally designed for agricultural use but due to the relatively low cost and promising spectral variety we decided to use them as a supplement in our research approach. To achieve homogenous and sufficient image coverage of the whole study area we used the flight planning application *drone harmony* (https://droneharmony.com/) to create tailored flight plans. The research area was divided into four sectors in order to keep the UAV close enough to the respective takeoff points and save battery power by avoiding too strong ascents and descents. All four flight plans were designed with a front overlap of 80 percent and a side overlap of 70 percent while taking nadir pictures. Due to the steep terrain, we created a terrain-aware flight plan with a constant height of 60 m based on a digital terrain model. Data collection with the unmanned aerial vehicle resulted in more than 5800 RGB-images and roughly 4000 images from each multispectral camera. The imagery has an average ground sampling distance (GSD) of 1.85 cm/pixel for the onboard RGB-camera and a GSD of 2.25 cm/pixel for the multispectral cameras.

Data processing

Data processing was undertaken separately for the RGB imagery and the multispectral imagery. The multispectral pictures needed to be preprocessed and calibrated in the software application *MAPIR Camera Control*, turning the recorded pixel values into reflection values for the respective bands. Then, the captured RAW and JPEG images were combined to TIFF images.

The photogrammetric processing procedure (Structure from Motion) in *Agisoft Metashape* (https://www.agisoft.com/) followed the workflow described by the United States Geological Survey (USGS National UAS Project Office 2017) and modified in line with on-site experience. The modifications included removing the camera positions before the alignment process to minimize matching issues, using filtering options customized to the data, and building the orthomosaic on the basis of the DEM which is reliable for aerial surveys. The workflow was carried out using high settings in the Agisoft dialogues with the same configurations for each set of images. Adaptive camera model fitting was activated and low-quality pictures were removed beforehand. Image quality was assessed inside Agisoft with a drop-out threshold of <0.5. The project was rectified and georeferenced using 39 ground control points, of which nine were used as check points for uncertainty estimation. The following table shows the uncertainty values (RMSE) for the control points and check points:

Table 1: Uncertainty values: The RMSE for the control points and check points.

	Count	**X error (cm)**	**Y error (cm)**	**Z error (cm)**	**XY error (cm)**	**Total (cm)**
Control points	30	3.20	3.27	5.44	4.58	7.11
Check points	9	3.66	4.37	5.53	5.70	7.94

The derived products from the photogrammetric processing in Agisoft were:

- Digital elevation model (from RGB imagery, spatial resolution: 10 cm/pixel)
- True color orthomosaic (from RGB imagery, spatial resolution: 4.5 cm/pixel)
- False color orthomosaic (from OCN imagery, spatial resolution: 4.5 cm/pixel)
- False color orthomosaic (from RE imagery, spatial resolution: 4.5 cm/pixel)

Changing weather conditions led to variations in the illumination of the recorded pictures and to inconsistent brightness values across the final orthomosaic. This caused difficulties in the further course of the classification procedure.

Random Forest image classification

A Random Forest (RF) machine learning algorithm was chosen to classify the vegetation based on the orthomosaics because of its robust and reliable functionality. Random Forest has proven very successful for comparable applications in the field of land cover classification and vegetation mapping (Colditz 2015, Daryaei et al. 2020, Haas & Ban 2014, Van Beijma et al. 2014). The Random Forest classifier makes predictions based on a set of classification and regression trees (CARTs) and is insensitive to overfitting and robust when handling inconsistencies in spectral response (Briem et al. 2002, Miao et al. 2012, Guan et al. 2013, Belgiu & Drăguţ 2016, Liu et al. 2011).

The number of trees used is one of the parameters needed to be fixed by the user and usually improves model performance when being increased. A bagging approach is used which means that each classifier in the ensemble is trained with a randomly chosen subset of samples. How many samples are used in this step is also defined by the user. In the course of this, specific training samples might be used several times during the tree creation process while others might not be considered at all. The created trees have a high variance and a low bias. Additionally, roughly one third of the samples is automatically used for an internal cross-validation measuring the model performance (Breiman 2001). During the classification process each tree votes for one class and the class with the most votes becomes the one selected as the final classification output (Belgiu & Drăguţ 2016).

Bagging ensemble methods like RF perform better in remote sensing classification tasks than single classifiers because they do not expect the data to be normally distributed such as supervised parametric classifiers like Maximum Likelihood Classification do (Liu et al. 2011). As a rule, RF algorithms achieve higher accuracies with an increasing number of trees and therefore this value could be theoretically incremented excessively (Guan et al. 2013). Care must be taken that the required computational resources also grow in a linear rate with a higher number of trees. Different studies, however, show that constantly increasing the number of trees does not necessarily lead to a better model performance. Above a certain number of trees, no significant improvements were detectable (Du et al. 2015, Topouzelis & Psyllos 2012).

In this work class balance and a high target representation were ensured by skilled personnel manually selecting samples directly from the highly resolved orthomosaic. To warrant independent validation data, 20 % of the samples were excluded from the training process and used for validation after the classification process. These samples were chosen randomly from the entirety of samples to avoid any kind of bias. 3345 samples were digitized by hand from which 2686 were used for training and 659 for validation.

We distinguished between nine land cover classes that were defined as follows:

Table 2: Land cover classes and number of ground truthing samples used for the classification.

Class value	Class description	Number of samples
1	Snow	423
2	Water	307
3	Bedrock	399
4	Coarse sediment	585
5	Fine sediment	305
6	Juniper (*Juniperus communis*)	300
7	Thistle (*Cirsium spinosissimum)*	399
8	Mixed vegetation with > 50 % grass	310
9	Mixed vegetation with > 50 % forbs and moss	317

Normally the Random Forest classifier is able to detect the variables which are most suitable for differentiating the predefined target classes but for this paper this step was performed by hand. This was because the RF-tool implemented in ArcGIS Pro does not offer this functionality and due to the low number of available variables. Training and classification were carried out with the implemented Random Forest algorithm in ArcGIS Pro. The appropriate number of trees for our analysis was determined by performing the classification procedure multiple times using identical settings except for the number of trees. For our final classification we used 100 trees and a tree depth of also 100. Except for the parameters we assessed ourselves, we followed the manufacturer's (ESRI 2022) recommendations, e.g. regarding the maximum number of samples per class that can be used, which is 1000 samples for unsegmented rasters. The training and classification processes were based on the RGB orthomosaic from which the samples were taken, utilizing the digital elevation model as an ancillary input dataset.

Results

The unmanned aerial vehicle (DJI Phantom 4 Pro V2.0) was able to carry the weight of three small-scale cameras, enabling us to record the area of interest with multiple sensors at the same time. The strong winds in the research area and the additional weight noticeably lowered the flight time of the UAV and led to unstable flight conditions at some points (e.g. unexpected descent of the aircraft, difficulties compensating vibrations and wobbling). However, our research shows that it is possible to successfully perform aerial surveys in proglacial areas using consumer-grade UAVs. This statement holds true because modern UAVs feature higher battery capacities and provide better flight performances than the model we used. Difficulties occurred when using the low-cost multispectral cameras from MAPIR. The included mount could be fixed properly on the UAV but the integrated vibration dampers did not meet the requirements of our application. Blurring and camera shake were visible on many of the captured images although we paid attention to the camera settings (shutter speed, ISO value). Changing illumination conditions during the survey could not be eliminated using the MAPIR calibration target. Fluctuations in brightness influenced the reflection values of the multispectral imagery more strongly than the actual variance in vegetation on the ground (see Figure 3 and 4).

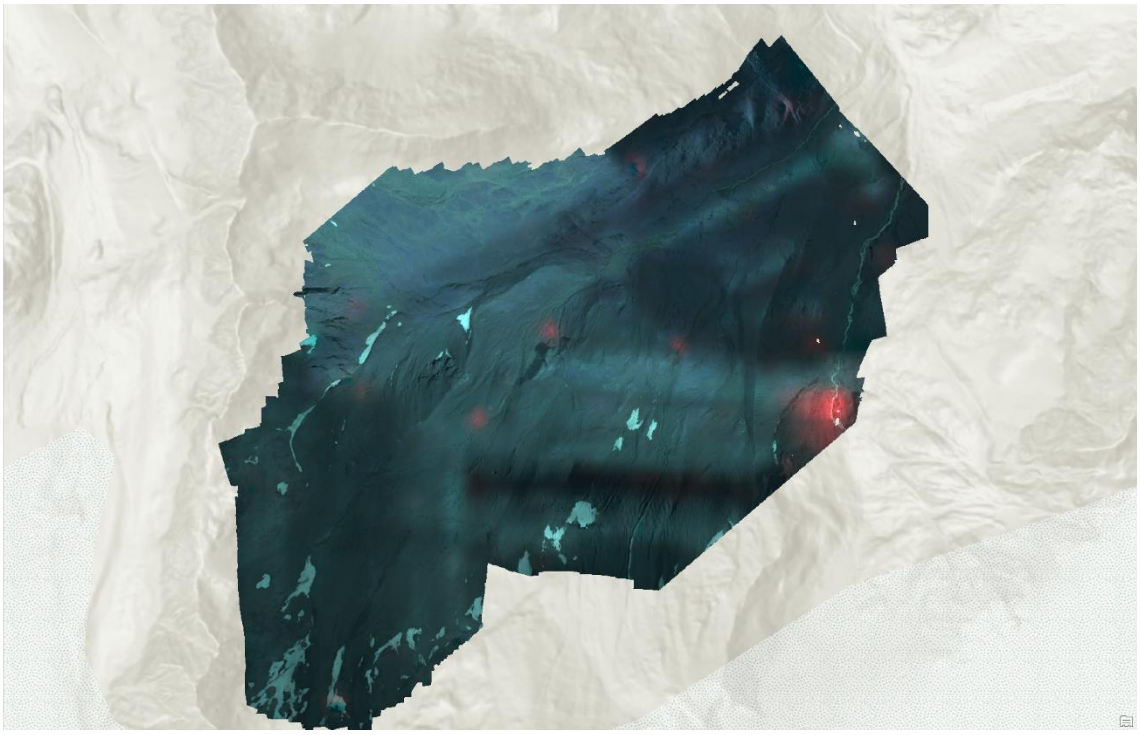

Figure 3: OCN orthomosaic. The OCN orthomosaic was heavily impaired by unstable illumination conditions. (Zangerl 2020).

Figure 4: Red edge orthomosaic. The red edge orthomosaic showed even stronger detriments caused by unstable illumination conditions than the OCN orthomosaic. (Zangerl 2020).

The classification results demonstrate a predominance of non-vegetated areas in the study area (> 70 %) with coarse sediment as the most common class (> 30 %). Figure 5 shows the geographical distribution of the detected classes and Table 3 presents the results in absolute and relative values.

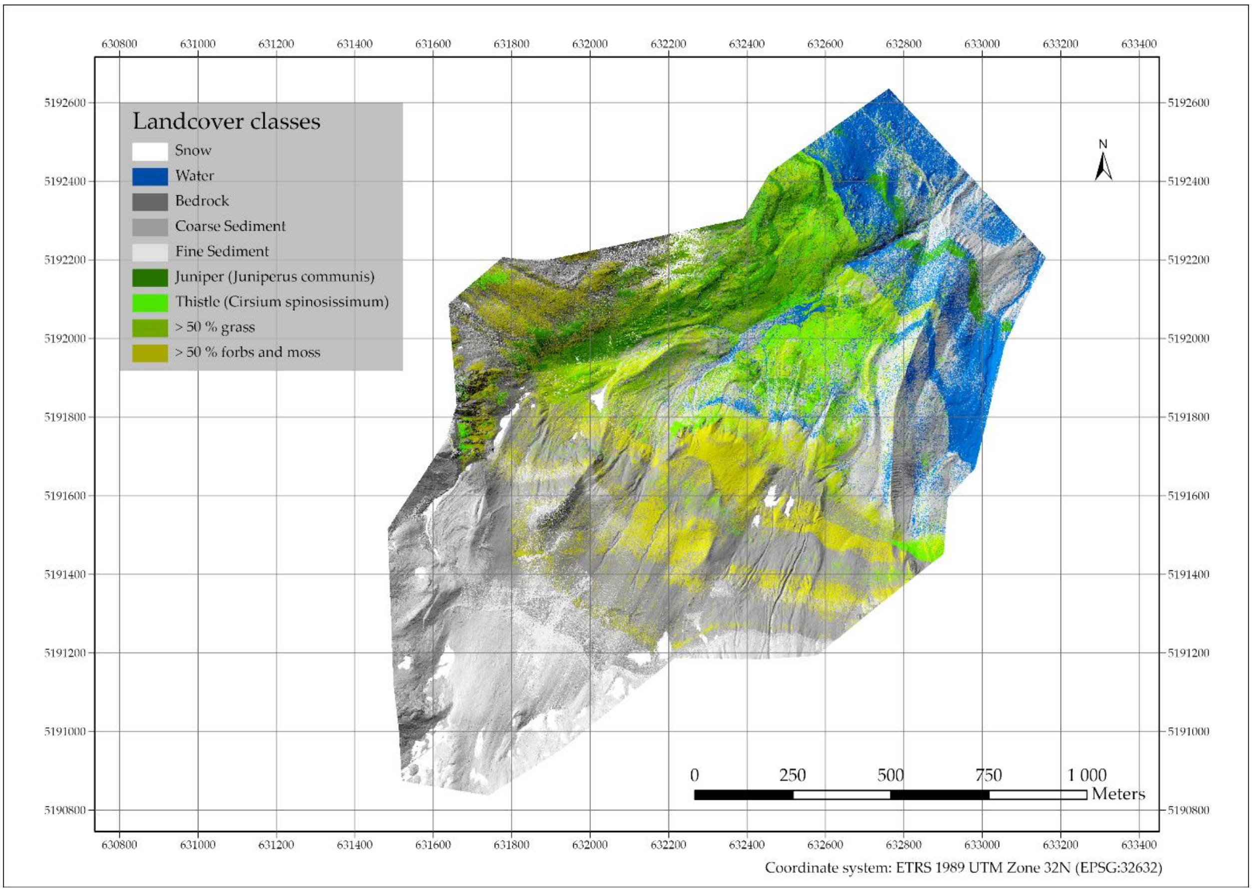

Figure 5: Classification results (visual). Landcover classes in a high alpine valley in the Kaunertal. (Zangerl 2022).

Table 3: Classification results (textual). Total and relative distribution of the defined classes in the research area.

Class name	Total area (hectares)	Relative area (%)
Snow	5.38	423
Water	17.96	307
Bedrock	41.95	399
Coarse sediment	56.99	585
Fine sediment	4.47	305
Juniper (*Juniperus communis*)	6.26	300
Thistle (*Cirsium spinosissimum)*	7.75	399
Mixed vegetation with > 50 % grass	17.53	310
Mixed vegetation with > 50 % forbs and moss	18.29	317

The most highly evolved species, *Juniperus communis*, is mostly found in the northern part of the study area in lower regions and in particular on south-facing slopes that have been ice-free for at least 100 years. This statement is also true for the grass-dominated mixed-vegetation class. *Cirsium spinosissimum* often occurs in patches and always in areas with high ground humidity such as along streams, whereas the mixed vegetation class consisting of > 50 % forbs and moss is more dispersed and also occurs frequently in higher regions. The highest sections in the south-eastern part of the study area are dominated by large sediment fields and smaller interspersed snow patches, whereby the latter are obviously subject to rapid changes throughout the year.
Regardless of the terrain age, the most dominant vegetation class is "> 50 % forbs and moss" except for those regions that have been ice-free for more than 170 years. In this area the most common vegetation is grass ("> 50 % grass"). In areas which have been unglaciated for at least 100 years (terrain age > 170 years and terrain age < 170 years) the least common vegetation class is "Juniper", whereas in the two-remaining terrain-age classes the rarest vegetation form is grass. The youngest terrain in the highest part of the study area has been ice-free for roughly 50 years and is the only sector where not all vegetation classes are present. In this section no juniper was found at all.

Accuracy assessment

The best classification results were achieved using the RGB orthomosaic as the foundation of the classification and employing the digital elevation model for additional input data. The DEM was tested against the two available multispectral orthomosaics, the *Topographic Ruggedness Index* (TRI) and a slope layer and turned out to be the best supplement for this approach, as presented in Table 4.

Table 4: Supplementary datasets. This table presents the overall accuracy values reached for different supplementary layers when used in combination with the RGB orthomosaic in the classification.

Supplementary layer	**DEM**	**OCN**	**TRI**	**Slope**	**RE**	**No suppl. layer**
Overall accuracy (%)	87.1	73.1	73.0	70.9	69.2	67.0

The classification of the RGB orthomosaic in combination with the DEM achieved an overall accuracy of 87.1 %. In the approach where the OCN orthomosaic was used as a supplement the OA was considerably smaller with 73.1 %. When utilizing the Terrain Ruggedness Index layer, the OA was very similar with 73.0 %, while using the slope layer as an additional input resulted in an overall accuracy of 70.9 %. The red edge orthomosaic was the supplementary dataset which delivered the worst results with less than 70 % OA, a performance that was only slightly better than using no additional data with the RGB orthomosaic at all which resulted in an OA of 67 %.

The accuracy of the final classification was assessed by calculating a conventional confusion matrix resulting in the following statistical metrics: overall accuracy (OA), producer's accuracy (PA), user's accuracy (UA) and the Kappa Coefficient. The results of this evaluation are displayed in Table 5 showing the values from the most accurate classification (RGB + DEM):

Table 5: Accuracy Assessment. Confusion matrix displaying the accuracy values for each target class + overall accuracy, producer's accuracy, user's accuracy and Kappa Coefficient for the final classification.

Class name	Snow	Water	Bedrock	Coarse sed.	Fine sed.	Juniper	Thistle	> 50 % grass	> 50 % forbs & moss	Total	UA (%)	Kappa
Snow	77	0	1	3	1	0	0	0	0	82	**93.9**	0
Water	0	53	1	13	0	0	1	0	0	68	**77.9**	0
Bedrock	0	0	70	14	0	0	1	0	1	86	**81.4**	0
Coarse sed.	0	8	6	81	0	0	0	1	1	97	**83.5**	0
Fine sed.	1	0	1	3	60	0	0	0	0	65	**92.3**	0
Juniper	0	0	0	0	0	55	4	1	0	60	**91.7**	0
Thistle	0	0	0	2	0	3	69	4	3	81	**85.2**	0
> 50 % grass	0	0	0	0	0	2	2	51	0	55	**92.7**	0
> 50 % forbs & moss	0	0	1	2	0	0	2	2	58	65	**89.2**	0
Total	78	61	80	118	61	60	79	59	63	659	0.0	0
PA (%)	**98.7**	**86.9**	**87.5**	**68.6**	**98.4**	**91.7**	**87.3**	**86.4**	**92.1**	**0.0**	**87.1**	0.0
Kappa	0	0	0	0	0	0	0	0	0	0	0.0	**0.854**
OA (%)	**87.1**											

The Kappa value for the best model performance (RGB + DEM) is 0.854. The Kappa coefficient compares the classification results with randomly assigned values for each class. Therefore, one can derive how far a classification result is caused not by chance but by a good model performance. Kappa values of 0.6 – 0.8 are considered good and values above 0.8 indicate excellent model performance with very high concordance between the model and the actual ground truth (Liu et al. 2011).

In simple terms, the producer's accuracy and the user's accuracy describe the accuracy from the point of view of the map producer and the map user, respectively. This means that the producer's accuracy shows how often real features are correctly classified on the final map. User's accuracy, however, shows how often a classified value on the map will actually be present in reality (Humboldt State University 2019). In the case of class 4 ("coarse sediment") the producer's accuracy is the lowest with 68.6 %. We assume that this relatively high quota of misclassifications results from the visual resemblance between the three "rock" classes (bedrock, fine sediment, coarse sediment) which makes clear demarcations very difficult. This is not only true for the classification algorithm but also for the personnel digitizing the samples. As can be observed in the north and northeastern regions of the study area, a lot of water has been classified. In reality, most of these areas are covered with juniper. This error results from the beforementioned illumination problems during data acquisition. When flights were performed in this area, the sky was partially covered by clouds which resulted in darker images for this region. Training samples for the water class were also taken from the fringe areas of streams which are characterized by dark-greyish wet sediment. On the produced imagery, these wet rocks appear very much like the juniper bushes which were recorded in shadowed areas because the displayed structures bear a certain resemblance to one another. A negative influence resulting from changing illumination conditions can also be observed in the multispectral datasets, as seen in Figures 3 and 4, which is why these were excluded from the final classification procedure completely. Although vegetation patterns could be observed by eye especially on the OCN orthomosaic, the changing light incidence affected the reflection values to such an extent that these datasets eventually became unusable. Excluding the parts of the OCN orthomosaic with the heaviest impairment led to fewer misclassifications but still to a noticeably worse model performance than in the final approach.

The Random Forest tool implemented in ArcGIS Pro delivered satisfactory results in regard to landcover mapping and the vegetation cover. A limitation of this approach is the inability to add multiple supplementary datasets to the classification procedure at the same time. This makes determination of the variables which are most suitable for target class discrimination more time consuming and does not allow a multi-variable classification with more than two layers. However, the performance of training and classification tasks was reliable, including a built-in option for accuracy assessment using a confusion matrix. This makes the Random Forest tool in ArcGIS Pro a reliable, easy-to-handle and convenient method for landcover classification in sparsely vegetated areas, although its functionality is limited.

Discussion

Using a consumer-grade unmanned aerial vehicle to perform the surveys in this research turned out to be a sufficient approach even though minor problems occurred (reduced flight time partly caused by the additional payload and difficulties in stabilizing the aircraft during strong winds). Given the additional weight on the aircraft and the rough environmental conditions in our research area these problems might not arise in a different setting such as a lower altitude study area and when using an unmodified UAV. To some extent, the limited battery capacity is an issue that still pertains to other settings and restricts the maximum area that can be monitored. If it takes several days to record the whole area of interest (like in our case), there is an increased risk of unstable weather conditions which might negatively influence the picture quality (e.g. varying illumination conditions, fog on images). Due to the large area of interest that needed to be covered by our UAV survey, the creation of multiple flight plans helped to reduce energy consumption and made the flights more efficient. However, we suspect that the arrangement of the flight plans led to difficulties in the further processing steps. Although we ensured a steady image overlap within the individual flight plans, the overlap between the different flight plans was not always sufficient. We consider this as a possible source of the errors that arose in the elevation data during photogrammetric processing. Geometrical artefacts looking somewhat like rocks appeared in the digital elevation model (see Figure 6). Some of them occurred in linear structures in regions where the flight plans adjoined one an-other. Using the *Depth Maps* instead of the dense point cloud for the DEM generation in Agisoft resolved this problem (see Figure 7) but the origin of these errors could not be explicitly determined. We assume that the imperfect overlap between the flight plans and patches of fog that moved through the study area while performing the UAV flights created noise in the point cloud that could not be eliminated by filtering.

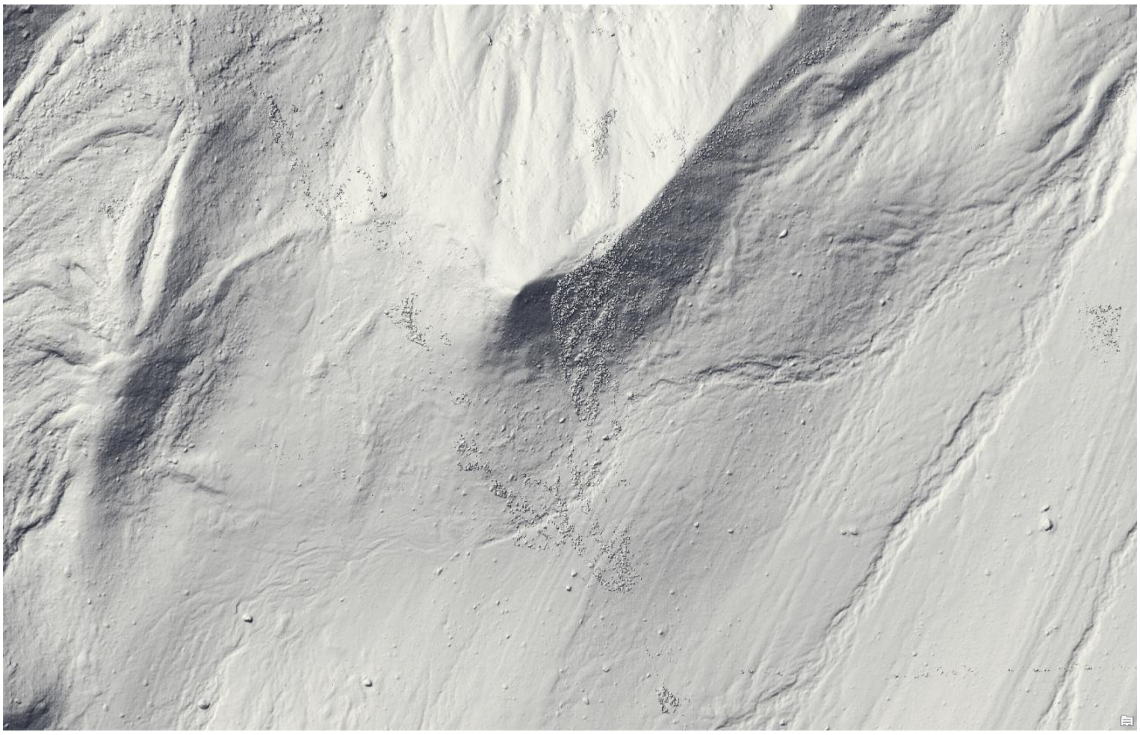

Figure 6: DEM with artefacts. Geometrical artefacts occurred in the elevation model during photogrammetric processing. (Zangerl 2020).

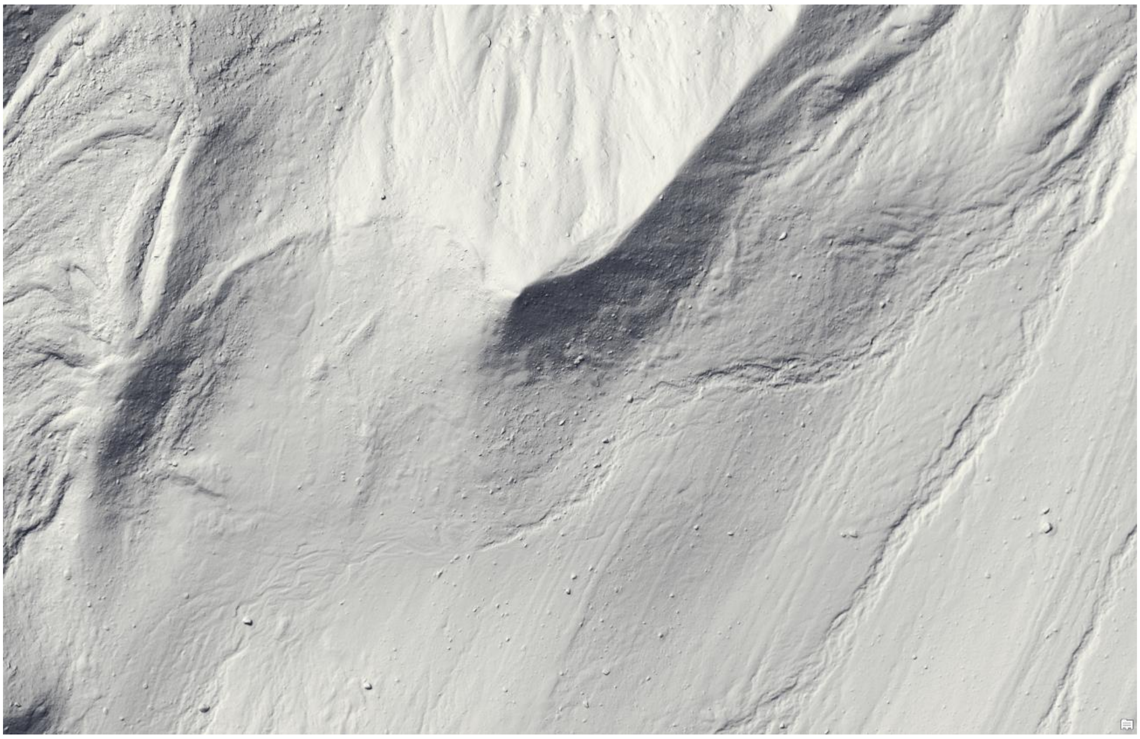

Figure 7: Adjusted DEM. The artefacts could be removed by using the *Depth Maps* for the DEM creation. (Zangerl 2020).

We view the use of low-cost multispectral cameras for classifying vegetation in pro-glacial areas very critically because the cameras we employed did not deliver satisfactory results for our use case. The beforementioned illumination problems occurred more severely on the multispectral imagery than on the RGB imagery even though the intended calibration target was used. Employing a superior mount for the multispectral cameras might lead to an improvement because of less blur in the pictures but the problem of the high sensitivity towards illumination fluctuations still persists.

One of the biggest challenges in classification tasks is the categorization of present features into target classes. Some kind of generalization based on the corresponding characteristics of these features was needed to meet the demands of a worthwhile classification. This generalization was undertaken by experts in order to represent the given circumstances in a manageable number of classes without losing too much detail on the one hand or overstraining the classification algorithm with overly high demands on the other hand. The maximum accuracy of a classification is always limited and hard to predict in advance. This holds true specifically for landcover classifications and vegetation mapping because it is impossible for the researcher to say with certainty which classes will be distinguishable prior to planning the survey. In our case, this complicated the formation of target classes even more. We tried to classify the existent vegetation in as much detail as possible because we knew that we were limited by the resolution of our data anyway. Investigation of the processed imagery revealed that it was only possible to base a distinction on species for the largest plants growing in our research area. Thus, the classes “Juniper (Juniperus communis)” and “Thistle (Cirsium spinosissimum)” are the only classes that actually describe single species while the remaining vegetation was aggregated into mixed vegetation classes (“> 50 % grass” and “> 50 % forbs and moss”). The inconsistency of the class formations brought further difficulties because underdeveloped specimens of thistles and junipers might have been included in the mixed vegetation classes as well. A sharp demarcation among the mixed vegetation classes was hard to achieve because the actual size of the plants often fell below the spatial resolution of our imagery. This complicated the creation of training samples for the researchers and lowered the preciseness of the classification. Similar complications occurred with the non-vegetation classes, which were rather coarse. The difficulty of fuzzily defined class-borders occurred between the sediment classes (“bedrock”, “coarse sediment”, “fine sediment”) which were impossible to

separate definitely because of strong overlaps. Another factor to which attention must be paid is the volatility of the “snow”-class which changes dramatically during the year and always covers some of the other target classes.
With all of these restrictions in mind, one must be aware that a landcover classification always resembles a coarser and temporally fixed reflection of reality. This kind of approach still delivers valuable information on the area of interest and is able to function as the basis for a wide range of further analyses. Accepting a certain degree of uncertainties is always part of the game.

Performance of the landcover classification carried out in ArcGIS Pro was gratifying considering the quality of some of the input data. The poor performance of the multispectral datasets can be traced back to the impairments caused by unstable illumination conditions during data acquisition but not to the classifier’s performance itself. We therefore consider this a fast and easy-to-use approach for landcover classification and vegetation mapping that is well applicable for surveys with a low number of input variables. One of the biggest drawbacks of the approach are the limited options regarding multi-layer analysis. This leads us to the conclusion that for explorations with a high number of variables a different framework like *R* would likely perform better and is also more convenient in regards of automatization.

Conclusions

We conclude that the use of unmanned aerial vehicles in combination with the Random Forest classification algorithm is a suitable approach for detecting sparse vegetation in proglacial areas. Photogrammetrically processed drone-imagery provides a sufficient backbone for robust land cover classification. A limiting factor for UAVs is the battery capacity and therefore the maximum size of the study area. With an extended surveying time the risk of changing weather conditions also increases which leads to major problems regarding the recorded reflection values (especially on multispectral imagery). Multispectral data from consumer grade cameras might offer an added value to vegetation classifications if the quality is sufficient. We found that this kind of imagery is even more sensitive to variations in light than RGB imagery. Using a calibration target reduces the illumination problems but was still not satisfactory in our case. Employing a better mount for the multispectral cameras might improve the image quality as this can reduce blur. Care must be taken as installing additional cameras on a UAV with a low payload impairs the drone's flying behavior significantly, even with an appropriate mount. Defining target classes for the classification procedure is a crucial step that deserves special attention. The distinction of said classes might be challenging because of overlaps between the classes and features which are smaller than the ground sampling distance of the data.

The vast majority of our research area is unvegetated and covered largely in coarse sediment. The measured distribution of the vegetation in our study area meets our expectations and has a high overall accuracy of 87.1 %. The most highly evolved species (Juniperus communis) was mostly found in lower and sunnier regions. Forbs and mosses formed the most common vegetation and were present in all parts of the research area whereas thistles (Cirsium spinosissimum) were primarily found in moist areas.

Severe degradation of the multispectral data forced us to exclude it from the analysis but using only RGB-imagery in the Random Forest algorithm proved time-efficient and reliable. The implemented RF tool in ArcGIS Pro is a suitable approach for detecting sparse vegetation in alpine areas if a low number of variables are used. The combination of the RGB orthomosaic and the digital elevation model produced the best results.

Recommended actions for future research:

- In cases where battery capacity plays a major role (because of a large study area or additional weight on the aircraft) or when flying under windy conditions the use of an enterprise-segment UAV with a higher payload and more wind stability is recommended.
- When dividing the research area into several flight plans, attention must be paid to sufficient image overlap not only within the flights plans but also between them. Linear artefacts in the photogrammetric products may occur in the border regions if this is neglected.
- Illumination conditions play a major role in UAV surveys and should therefore be a primary consideration. UAV operators are advised to perform their fieldwork under steady weather conditions and to try to maintain consistent illumination of the study area throughout all flights.
- When defining target classes, care should be taken to maintain a sharp distinctiveness of the samples, not only in the field but also on the processed orthoimage. This should lead to fewer misclassifications and reduced fuzziness of the final results.
- Increasing the spatial resolution of the UAV imagery (by flying at a lower altitude or using a different camera setup) also increases the ground sampling distance of the final orthomosaic, which allows a more precise classification (especially of small features).
- For multi-layer classification tasks, we recommend using a different framework than ArcGIS Pro when applying the Random Forest algorithm, one which can include a high number of variables at the same time.

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