UAV-Based Multispectral Data for Tree Species Classification and Tree Vitality Analysis

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Abstract: The presented research work tested the suitability of remote sensing via unmanned aerial vehicles (UAV) and multispectral data as a low-cost solution for forestry applications. High-resolution 6-band multispectral aerial image sequences obtained via UAV acquisition flights in three research areas in Austria were photogrammetrically processed to coherent datasets by the use of Structure-from-Motion technology. Resulting orthomosaics, digital surface and digital terrain models in resolutions from 2.5 – 5 cm were utilised in the subsequent object-based image analysis combined with a Random Forest classification modelling approach. The methodology facilitated tree species classification and vitality analysis with additional predictive mapping.

Our study delivered promising results for the application of UAV-based multispectral datasets in operational forestry. The developed methodology performed reliably in species classification and despite inherent research issue-related uncertainties showed great potential in the detection of differences in tree vitality.

1 Introduction

Sustainable management of natural environments requires spatial information in high temporal and spatial resolution. Detailed information on tree species distribution and forest health represent essential parameters. Time-consuming terrestrial surveys are not able to provide near-term information on large scale and are often related to high costs. Forest management therefore widely relies on the supporting implementation of conventional remote sensing technology. Data obtained by earth observation satellites and aerial flight surveys are frequently used in forestry applications and are adequate for numerous research objectives (FASSNACHT et al. 2016; IMMITZER & ATZBERGER 2014; IMMITZER et al. 2012, 2018; IMMITZER et al. 2016a; IMMITZER et al. 2016b; LAUSCH et al. 2013). However, the mostly coarse resolution of freely available satellite imagery of earth-orbiting satellites as well as complex planning and high costs of airplane-based surveys restrict their applicability for several investigations and research approaches. Furthermore, strong weather-dependency, for example in recurrent overcast conditions, diminishes the reliability of data supply.

In times of climate change, flexibility is of crucial importance when monitoring forest disturbances like bark beetle (IMMITZER & ATZBERGER 2014) or fungus infestations (KIRISITS & FREINSCHLAG

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2012) in order to develop mitigation strategies and initiate timely countermeasures. Changing climatic conditions and resulting severe weather events increase the vulnerability of trees (FACCOLI 2009) and thus infestation risk (FAHSE & HEURICH 2011; IMMITZER & ATZBERGER 2014; LINDNER et al. 2010). The development of suitable monitoring methods for the localisation of stressed and hence potential host trees or outbreak epicentres has gained largely in importance.
Gathering information about tree species distribution in forest management systems that approximate close-to-nature silvicultural practices is of utmost interest. The development towards ecologically and politically preferred heterogeneous mixed forests over pure stands entails traditional field-based assessment methodologies for tree species distribution, like stand estimation, as inapplicable. Generating operational forest inventories of these mixed forests requires cost-effective and accurate acquisition of detailed information on species distribution (GOODBODY et al. 2017).
Numerous scientific publications indicate the introduction of a flexible low-cost solution in unmanned aerial vehicle-based (UAV) multispectral data acquisition and processing for multitemporal monitoring of forest disturbances and species distribution mapping (FRANKLIN & AHMED 2017; FRANKLIN et al. 2017; GOODBODY et al. 2017; LEHMANN et al. 2015; LISEIN et al. 2015; MICHEZ et al. 2016; NÄSI et al. 2015; NEVALAINEN et al. 2017; TORRESAN et al. 2016). Application of UAV requires comparatively low planning efforts, as they are portable and easily deployed for data acquisition under suitable weather conditions and various terrains. Multispectral camera systems covering photosynthetically active wavelength spectra of visible light, as well as near infrared (NIR) parts of the electromagnetic spectrum in sub-decimetre resolution are highly suitable for the characterisation of vegetation and therefore described as an increasingly viable forestry application (GOODBODY et al. 2017; TORRESAN et al. 2016). Furthermore, they enable calculation of classification-enhancing raster layers like spectral band ratios, vegetation indices, variance-based metrics (e.g. PCA – principal component analysis) or structural indices.
The study aims to develop an object-based Random Forest (RF) modelling approach for tree species classification and vitality analysis based on UAV-based multispectral imagery from three investigation sites in Austria. Image datasets were obtained from an European ash (*Fraxinus excelsior*, L.) seed plantation where the fungal pathogen *Hymenoscyphus pseudoalbidus* causes ash dieback disease, a stand of Norway spruce (*Picea abies*, (L) Karst.) with a monitored infestation by the European spruce bark beetle, and a heterogeneous mixed forest stand. We explore suitability and limitations of obtained image datasets and evaluate the applicability of multispectral image data and applied methodology in regard to respective research questions:

1) Are differences in vitality of individual European ash trees detectable using multispectral UAV-imagery and applied methodology, and how well do the results explain reference data from a ground-based damage assessment?
2) Is it possible to reliably differentiate infested from not infested Norway spruce trees with the multispectral UAV-imagery and applied methods?
3) Is a sufficiently accurate tree species classification and distribution mapping feasible on the basis of present image data and developed methods?

2 Methodology

The workflow of the presented research work is divided into different thematic sections, such as data acquisition via UAV flights, photogrammetric processing of the obtained image sequences, and object-based image analysis with RF classification which is finally used for predictive mapping (Fig. 1).

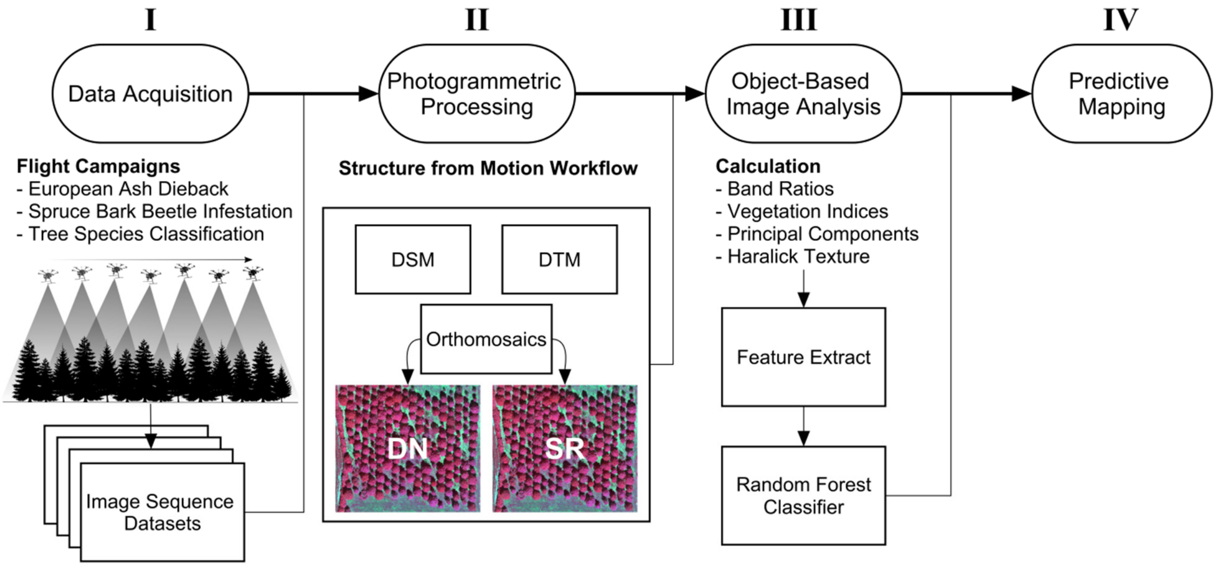

Fig. 1: General workflow showing main steps of the conducted research project

2.1 Investigation Areas

The investigated seed plantation of European ash was established close to Feldkirchen an der Donau, a municipality in the Austrian state of Upper Austria. The area is situated at 48°20'13.4"N, 14°02'50.2"E and has an average altitude of 270 m above the Adriatic (m AA). Averaged annual rainfall quantity stretches from 53.5 mm in February to a maximum of 124.9 mm in July. The flat area is characterised by hardwood floodplain forests along the river Danube in the south and the mountainous region of Mühlviertel in the north.

Decreasing tree population size due to ash dieback disease caused by the fungal infection with *Hymenoscyphus pseudoalbidus* is a known and widespread problem in Austria since it was first reported in 2005 (HALMSCHLAGER & KIRISITS 2008). The severity of the disease is ubiquitous and threatens the future of the European ash as an economically and also ecologically valuable tree species (KIRISITS & FREINSCHLAG 2012). Concerned with the possible extinction of the European ash, researchers established several seed plantations to conduct research on clones of individual ash trees with desirable traits for timber production, which could express signs of natural genetic resistance towards the pathogenic fungus.

The Norway spruce stand (48°53'12.1"N, 15°09'48.6"E), infested by the European spruce bark beetle, and the mixed forest stand proposed for tree species classification (48°52'32.6"N, 15°09'13.5"E) are situated near Heidenreichstein in the northwestern part of the Waldviertel region within the Austrian state Lower Austria. Located at an average altitude of 620 m AA, bedrocks of the plateau region are mainly base-poor silicates and prevalent climate conditions are considered continental (PROVINCIAL GOVERNMENT OF LOWER AUSTRIA 2015). According to ZAMG (2018), annual mean precipitation in the Waldviertel region only amounts to 400 mm with a maximum of 100 mm in July. Due to low precipitation and temperature increase in spring and summer, spruce stands in this area are endangered by insect pests like European spruce bark beetle or Spruce wood engraver.

Before countermeasures in form of tree extractions were carried out, reference data on infested and healthy spruces were collected for the purpose of testing detectability of differences in tree vitality with the acquired multispectral images for the whole stand (N = 652).

In the mixed forest stand, Norway spruce and Scots pine (*Pinus sylvestris*, *L.*) can be regarded as the predominant species. European silver fir (*Abies alba*, *Mill.*) is also occurring in large numbers, whereas European beech (*Fagus sylvatica*, *L.*) and European larch (*Larix decidua*, *Mill.*) were present with 13 and 9 individuals respectively. Multispectral images of the area were recorded for the development of a tree species classification and segmentation approach for small-scale species distribution mapping.

2.2 Data Acquisition

We utilised a modified DJI S900 lightweight multirotor UAV equipped with the multispectral camera AIRPHEN (Focal length: 8 mm; Resolution: 1280 x 960 pixel), comprising six synchronized global shutter sensors arranged in a 2 x 3 array for multispectral image acquisitions. Recording wavelengths were predefined at 450 nm (BLUE), 570 nm (GREEN), 675 nm (RED), 710 nm (RED EDGE 1), 750 nm (RED EDGE 2) and 850 nm (NIR). A linked GPS antenna added positional information to the image metadata and facilitated and enhanced subsequent steps in the photogrammetric image processing. Flight planning ensured a front-overlap of 80 % with a side-overlap of 40 % of the image size. Images were captured in an interval of 2 seconds at a flight speed of 3 m/s (KRAUSE et al. 2016). Spectral reference measurements were taken with a calibrated PSR-2500 full range portable spectroradiometer using differently coloured felt targets in white, black, light grey, dark grey, light green and dark green. Calibration data was used for correcting the obtained imagery to reflectance values during the photogrammetric image processing.

2.3 Photogrammetric Processing

Photogrammetric image processing was realised in Agisoft PhotoScan Professional 1.3.2, developed by Agisoft LLC, St. Petersburg, Russia. This software provides an automated image processing pipeline for aerial imagery using Structure from Motion technology which is widely applied in recent forestry-related research (DANDOIS & ELLIS 2013; LEHMANN et al. 2015; LISEIN et al. 2015; MOHAN et al. 2017; NÄSI et al. 2015; TOMAŠTÍK et al. 2017; TORRESAN et al. 2016). The image sequences were processed into coherent datasets, providing structural as well as spectral information in the form of a digital surface model, a digital terrain model and reflectance orthomosaics of each investigation area.

2.4 Object-Based Image Analysis (OBIA)

Processing and modelling procedures for the OBIA workflow have been developed within the open-source environment of RStudio (Version 1.0.153) (RSTUDIO TEAM 2016) using the open-source statistical programming language R (Version 3.4.3) (R CORE TEAM 2017). Map products of this study were created using ESRI ArcGIS® ArcMap 10.3 software, which was also used for digitising procedures.

Image analysis and modelling approaches were developed (Fig. 2) using the following R packages: *randomForest v4.6-12* (LIAW & WIENER 2002); *raster* (HIJMANS 2017); *caret* (KUHN et al. 2017); *matrixStats* (BENGTSSON 2017). Additionally, the open-source software Orfeo ToolBox (OTB Version 6.2.0) (MICHEL et al. 2015) was utilised via system commands in RStudio for tree crown segmentation trials with Large-Scale-Mean-Shift (LSMS) algorithm and the calculation of Haralick textural features.

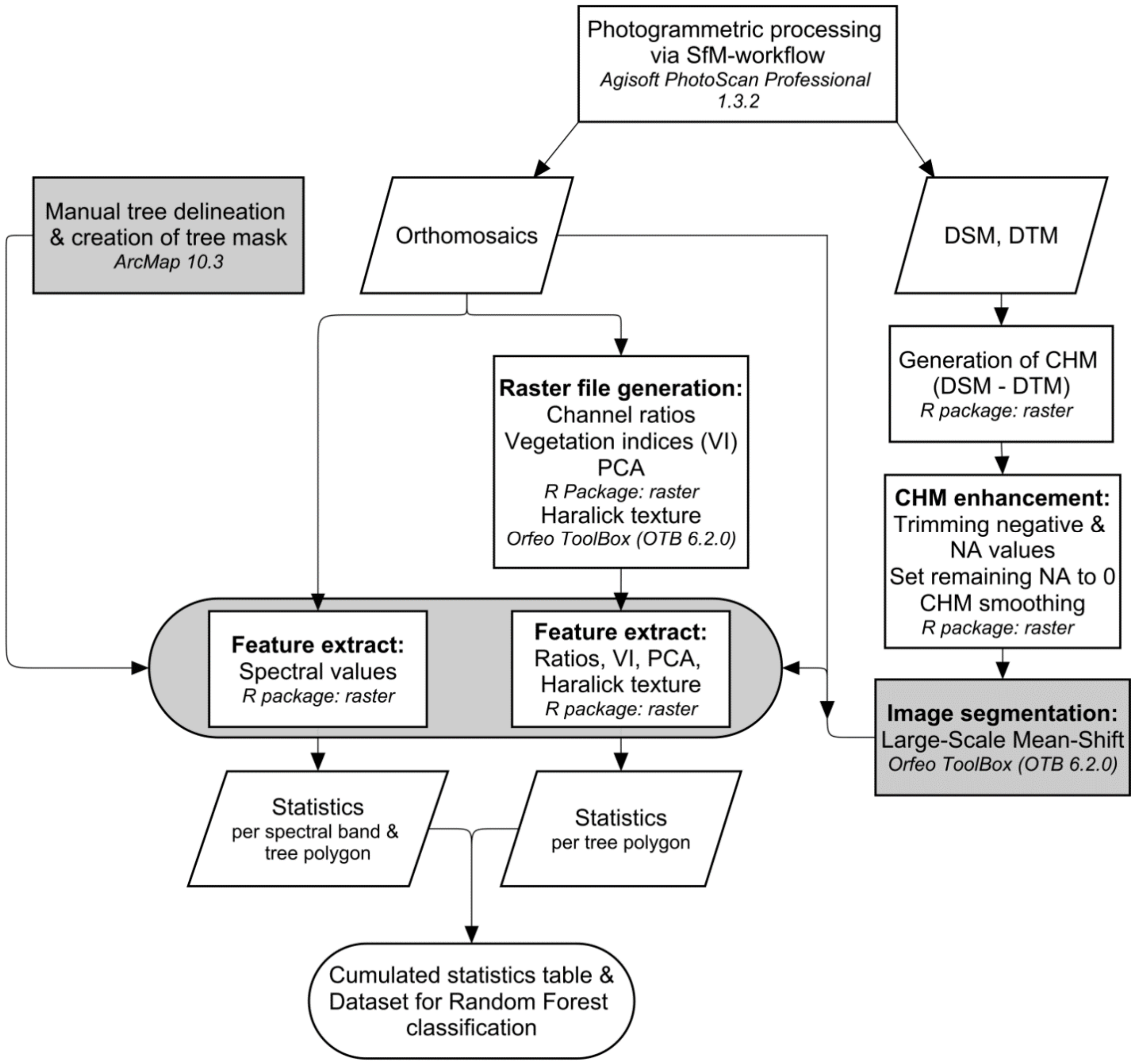

Fig. 2: OBIA workflow showing detailed steps of image data processing with reference to applied software packages

2.5 Training Polygons & Segmentation

Individually selected trees were manually delineated on colour-infrared orthomosaics and digitised in ESRI ArcMap 10.3. Resulting crown polygon shapes, including illuminated as well as shadowed crown parts, served as masks for the ensuing OBIA feature extraction process. Branches in lower tree levels or transition areas to adjacent trees were excluded.

Sunny conditions during data acquisition at the species classification site and resulting directional shadowing effects generated large inhomogeneity in radiometric values at crown level. To account for expected misclassifications, a mixed shade class was introduced, which considered independent of the surrounding tree species. Additionally, trees were delineated by using Large-Scale Mean-Shift (LSMS) segmentation in an attempt to automatize ensuing predictive mapping. The LSMS segmentation from the Orfeo ToolBox (MICHEL et al. 2015) was used via system commands in Rstudio. Numerous other vegetation-based remote sensing applications using the LSMS method (EINZMANN et al. 2017; IMMITZER et al. 2016b; NG et al. 2016, 2017) already presented excellent results.

2.6 Feature Layer Generation & Data Extract

Based on the generated multilayer orthomosaics, several additional feature layers were calculated. Camera band settings allowed for spectral enhancement through calculation of 5 band ratios, 13 vegetation indices, as well as principal components (PCA) and Haralick textures that delivered additional datasets for enhanced classification procedures.

Tree crown polygons created for training and prediction (segmentation and manual digitizing) were utilised in the feature extraction using the *extract* function embedded in the *raster* package for R. Orthomosaics, feature layers from vegetation indices, as well as from PCA and Haralick texture feature calculation served as input for a data processing function that extracts data at locations with intersecting data and tree polygons. Based on extracted values, the following statistical measures were calculated for each individual tree polygon: *Mean*, *Standard Deviation*, *Median*, *75^{th}*, *90^{th}* and *95^{th} Percentile*. Compiled in a cumulative table, the derived statistics were used as a feature input dataset for the RF classifier.

2.7 Random Forest Classification

For the object-based classification of the extracted data, a RF (BREIMAN 2001) classifier was utilised. A recursive feature selection approach, which uses a stepwise elimination of the least important input features based on the particular *Mean Decrease Accuracy* ranking (importance measure), was applied (IMMITZER et al. 2016a; SCHULTZ et al. 2015; TOSCANI et al. 2013). In conclusion, the model with the lowest number of input features, reaching a minimum of 97.5 % of the maximum overall OOB (out-of-bag) accuracy, was declared as the best model (EINZMANN et al. 2017).

3 Results & Discussion

3.1 European Ash Seed Plantation

Five different ash dieback intensities (0 = no dieback, 1 = 0 – 5 %, 2 = 5 – 20 %, 3 = 20 – 50 %, 4 = 50 – 80 %) were classified with overall accuracies (OA) of 61.7 % (Tab. 1) in the European ash seed plantation. This result underperforms the overall accuracy of 71.0 % presented in another publication analysing ash damage class classification based on WorldView-2 data (WASER et al. 2014). Spectral in-class variability hampered the achievement of reliable classification results in the modelling procedure, which entails low correlation with the available reference data. It remains unclear if reference data from the ground-based assessment was inadequate for analysing differences that result from spectral datasets, or if the remotely sensed differences are related to other factors like intraspecific variability, thus such results do not reflect the damage intensity professionally assessed in the field. Therefore a final evaluation of our findings is difficult and requires further research.

Tab. 1: Confusion matrix of the best-performing RF model for ash damage classification

		Reference Data						
	CLASS	**0**	**1**	**2**	**3**	**4**	*Total*	*User´s accuracy*
Classification	**0**	19	9	0	1	0	29	65.5%
	1	21	79	15	4	0	119	66.4%
	2	0	5	4	4	1	14	28.6%
	3	0	2	4	2	1	9	22.2%
	4	0	0	0	0	4	4	100.0%
	Total	40	95	23	11	6	**175**	
	Producer´s accuracy	47.5%	83.2%	17.4%	18.2%	66.7%		
	Overall accuracy	**61.7%**						
	Kappa	**0.338**						

The binary logistic regression model for the differentiation of trees with damage rates below or above 5 % delivered satisfying results with an OA of 89.1 % (Tab. 2). Feature selection indicated good separability of the damage classes when utilising reflectance and Haralick texture measures based on RED and both RED EDGE spectral bands, as well as the Red Edge NDVI.

Tab. 2: Confusion matrix of RF model used in binary logistic regression
(0 = damage levels below 5 %; 1 = damage levels above 5 %)

		Reference Data			
	CLASS	**0**	**1**	*Total*	*User´s accuracy*
Classification	**0**	130	14	144	90.3%
	1	5	26	31	83.9%
	Total	135	40	**175**	
	Producer´s accuracy	96.3%	65.0%		
	Overall accuracy	**89.1%**			
	Kappa	**0.666**			

In reference to the first research question, differences in the vitality of individual European ash trees are very well detectable in the multispectral data. The detected differences do not correlate well with the in-field reference data from ground-based damage assessments of ash dieback.

3.2 European Spruce Bark Beetle Infestation

Results from the Norway spruce stand with a previously detected infestation with the European spruce bark beetle showed good separation of two reference-based training classes for *infested* and *not infested* individuals. The best Random Forest model reached an OA of 86.6 % with constant user's and producer's accuracies (Tab. 3). Thus it was subsequently used for predictive mapping (Fig. 3). Most features selected in the RF model process were based on red, red edge and NIR wavelengths, which underlines the importance of these spectral wavelengths for the detection of differences in vitality between individual trees (JONES & VAUGHAN 2010; LILLESAND et al. 2014; MASAITIS et al. 2013; OLLINGER 2011).

Tab. 3: Confusion matrix of RF model used in classification of infested and not infested spruces

		Reference Data			
	CLASS	**Not Infested**	**Infested**	*Total*	*User´s accuracy*
Classification	**Not Infested**	35	5	40	87.5%
	Infested	6	36	42	85.7%
	Total	41	41	**82**	
	Producer´s accuracy	85.4%	87.8%		
	Overall accuracy	**86.6%**			
	Kappa	**0.732**			

The majority of marked *infested* individual spruce trees are located along the main roads and a skidding trail at the northeastern border of the stand. This is likely related to a drainage canal alongside the road and the influence of road clearing measures in winter. The central area is predominantly classified as *not infested* with occasional *infested* tree clusters.

A verification of the predictive map (Fig. 3) was performed through professional in-field evaluation of the Norway spruce stand. In the entire stand, there were no further signs of bark beetle activity detected, which suggests a successful prevention measure of bark beetle propagation applied in the stand earlier. The formerly infested southwestern corner of the stand was completely cleared as a preventive countermeasure to avoid further dispersal of *Ips typographus* throughout the stand.

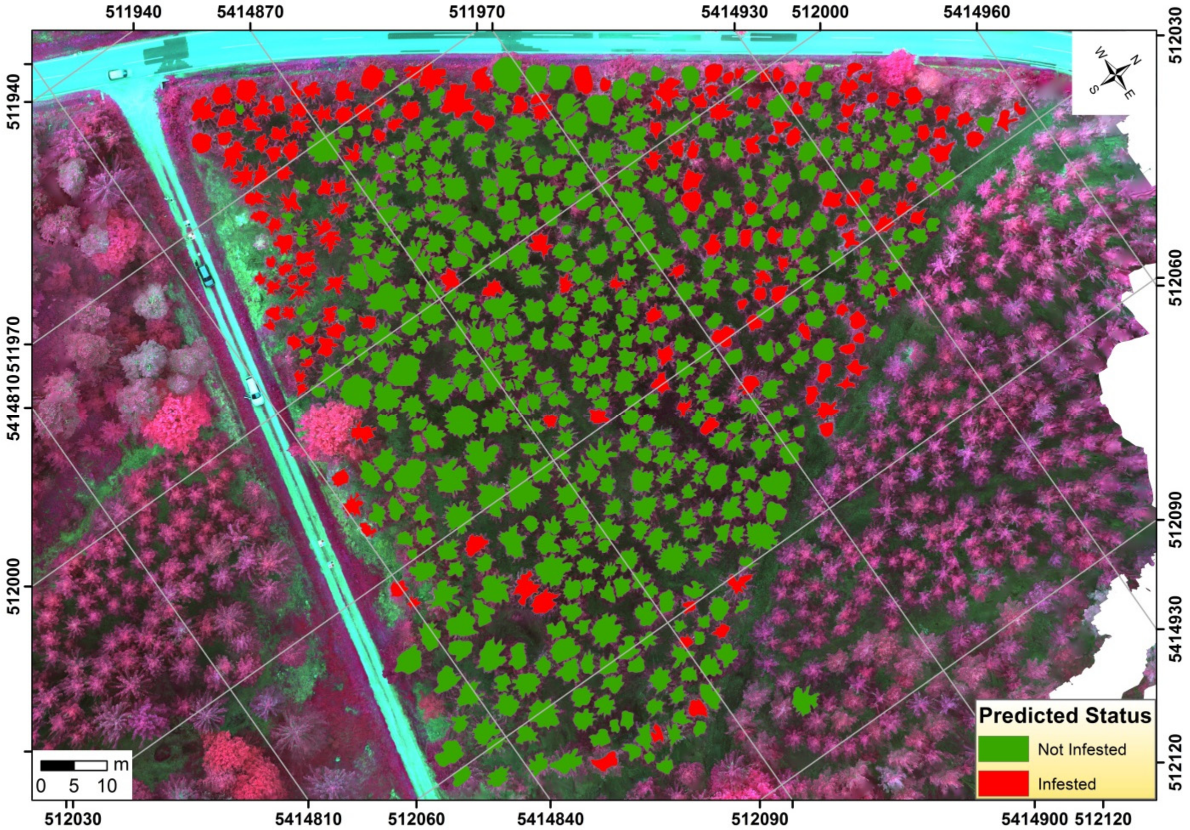

Fig. 3: Predictive distribution map for *infested* and *not infested* Norway spruce

During an in-field inspection, several characteristics that could explain signs of impaired fitness were detected. We discovered two marked trees with signs of mechanical bark damage and external resin flow, whereas surrounding trees that were classified as healthy did not show any signs of disturbance. Furthermore, three trees classified as *infested* have probably been naturally coppiced (top rupture or break of the central shoot) at a young life stage which led to growing of two main trunks as a result. Marked trees in other areas did not show any signs of stress that would be observable in a ground-based assessment. The extraction of two spruces with sparse crowns and one-directional crown growth for a professional examination of the bark and debarked wood did not show any signs of insect pest activity.

The detected tree stress-inducing conditions might affect reflectance characteristics at tree crown level, but assigning impaired fitness levels of tree crowns to certain disturbance factors remains difficult. Applying the designed and tested tree selection method, no infested tree remained undetected.

3.3 Tree Species Classification

Beyond the tested detection of infestations and spectral signals of diseases, our research delivered very satisfactory results for the individual species classification and spatial distribution mapping. Species differentiation methods developed in this study, based on UAV imagery, demonstrated plausible and promising results with a high OA of 95.8 % (Tab. 4). The lower producer's accuracy for European larch is likely due to the small sample size of the class.

Tab. 4: Confusion matrix of segment-based RF model used in predictive species distribution mapping

	Reference Data							
CLASS	**SPRUCE**	**PINE**	**LARCH**	**FIR**	**BEECH**	**SHADE**	*Total*	*User´s accuracy*
SPRUCE	29	1	2	1	0	0	33	87.9%
PINE	0	29	0	0	0	0	29	100.0%
LARCH	0	0	6	0	0	0	6	100.0%
FIR	0	0	0	29	0	0	29	100.0%
BEECH	1	0	0	0	13	0	14	92.9%
SHADE	0	0	1	0	0	30	31	96.8%
Total	30	30	9	30	13	30	**142**	
Producer´s accuracy	96.7%	96.7%	66.7%	96.7%	100.0%	100.0%		
Overall accuracy	**95.8%**							
Kappa	**0.948**							

As described in other publications, the spectral overlap of several species in the red edge and near-infrared band (Fig. 5) requires adding features to the model based on visible spectra. In blue wavelengths, the emissivity of European silver fir shows lower values than all other species, whereas Scots pine showed substantially lower reflectance in the GREEN band. The implementation of a Blue Ratio (WASER et al. 2014) and VDVI (WANG et al. 2015; XUE & SU 2017) in the RF model underlines the assumption of a good species separation potential in visible wavelengths. These findings are congruent with results of other studies on tree species classification (FENG et al. 2015; GITELSON et al. 2003; IMMITZER et al. 2012; IMMITZER, VUOLO, et al. 2016; NG et al. 2016). Contributing features based on red, red edge and near-infrared wavelengths were the multispectral indices RENDVI and NDRE.

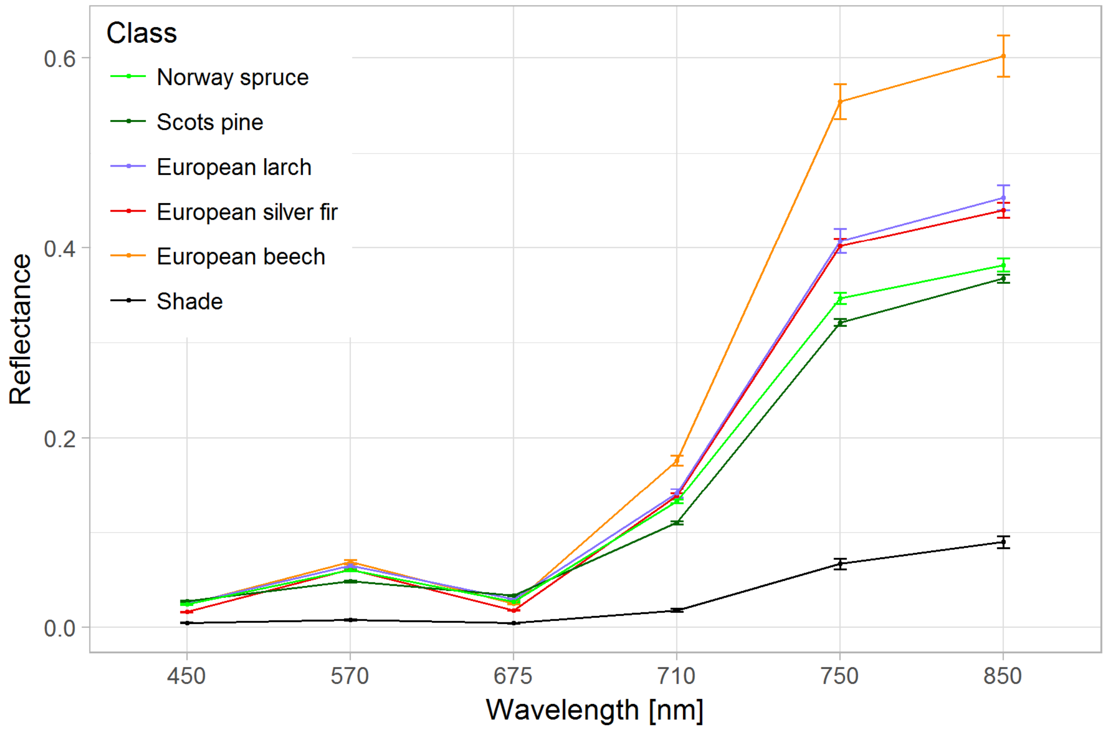

Fig. 4: Reflectance signatures of the five occurring tree species and shade class

In order to guarantee correct segment-based predictive mapping, the RF classifier was retrained with LSMS segments containing the centroids of the manually generated tree crown polygons. The evaluation of the resulting predictive species cover map (Fig. 4) showed remarkable congruency with ground reference from field observations.

Noteworthy overclassification in the predictive map was only observed in European larch, which shall be dispersed across the entire stand according to the predictive map (Fig. 5). In the course of the ground assessment individuals of European larch were only found in the northeastern quarter of the investigation area. Despite some other minor misclassifications like the confusion of a vigorous Norway spruce at the northern edge of the stand with the beech class, or intensely illuminated segments of coniferous tree crowns classified as European beech, the distinction between species showed reliable performance.

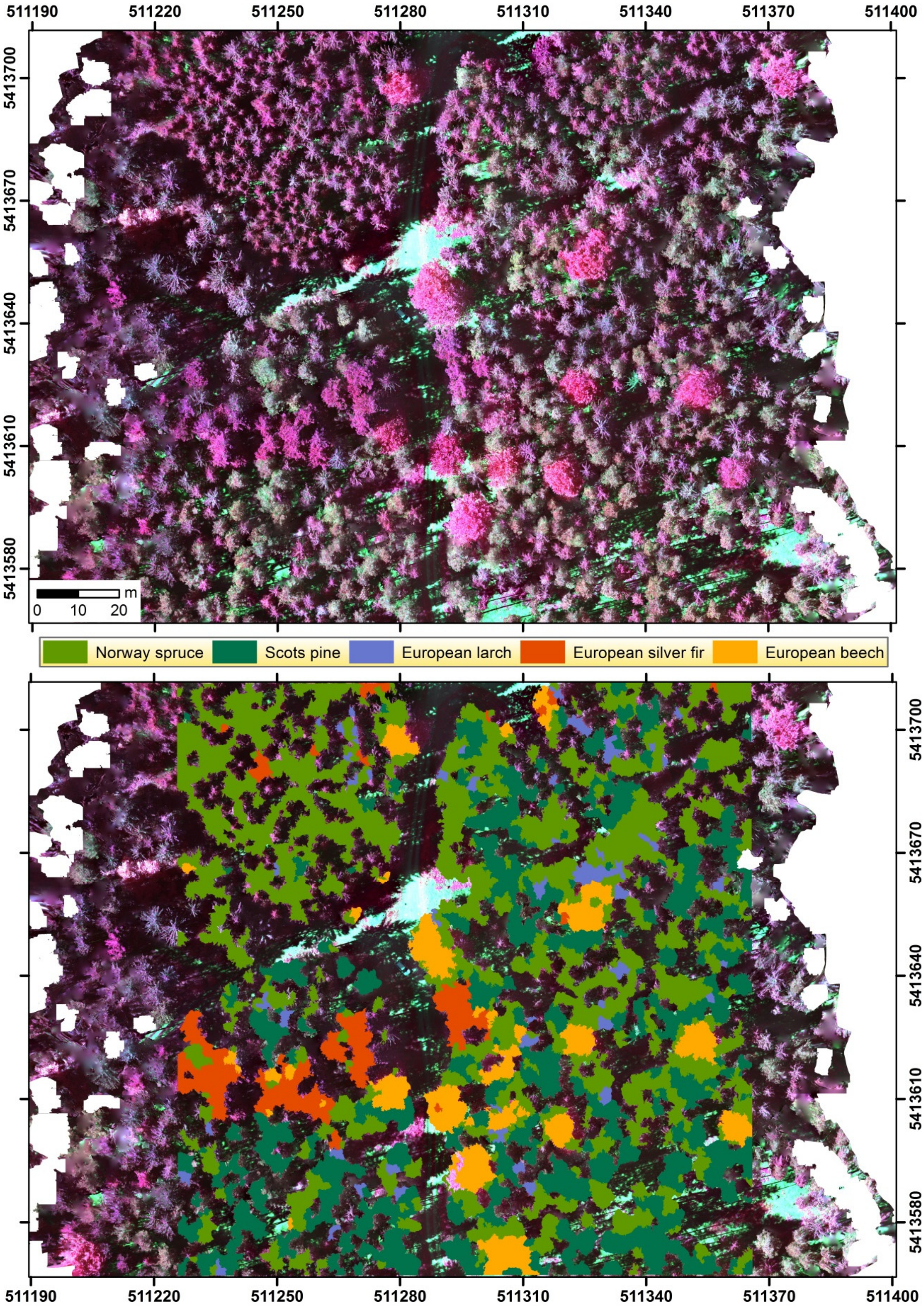

Fig. 5: Predictive species distribution map of tree species study site

4 Conclusion & Outlook

Our study results revealed high potential in the detection of infested or physiologically stressed trees, whereas an identification or assignment of the stress causes remains complicated and requires additional research. Concerning the species classification approach, our research delivered satisfactory results and achieved sufficiently accurate and reliable tree species classification and ensuing distribution mapping.

Feature selection showed that predictors based on red, red edge and near infrared reflectance were the most important ones for the detection of differences in tree vitality. This was similar for species classification which also relied on additional predictors based on reflectance in the visible region of the electromagnetic spectrum. From 18 tested band ratios and vegetation indices, only the PSRI, RENDVI, SAVI, NDRE, VDVI and Blue Ratio were used in the Random Forest classifier image processing method presented in this study. ADAMCZYK & OSBERGER (2015) mentioned differences in suitability of vegetation indices for threshold-based OBIA classification and the majority of selected indices in this study is also reported in other research publications (DASH et al. 2017; EINZMANN et al. 2017; WASER et al. 2014; XUE & SU 2017). Haralick texture indices were part of every best-performing Random Forest model which shows the importance and utility of textural information on crown level for classification of tree species and vitality differences.

Limitations in the spectral range covered by multispectral sensors might account for any of the occurring uncertainties. Earlier stages of physiological stress or smaller spectral differences could be detectable with better reliability using hyperspectral sensors that can observe physiological changes in wavelengths not covered by multispectral cameras. Hyperspectral cameras are however related to higher purchasing and operating costs. Additionally, the implementation of thermal imagery could enhance separability of different tree species and health conditions. Reflectance information from short-wave infrared (SWIR) and emissivity information from the thermal infrared (TIR) regions could emphasise characteristic differences for vitality analysis and species classification that are not perceivable with multispectral sensor equipment.

Altogether a significant reduction in expenses and the flexibility in application make UAV paired with multispectral sensor equipment a viable tool for the detailed remote sensing based monitoring of forested areas on small to medium scale. Hybridization of vertical take-off and landing and fixed-wing UAV are likely to expand the application range to much larger areas in the future (DEMPEWOLF et al. 2017). Furthermore, the technology could find use as a flexible support for established satellite remote sensing systems (e.g. Sentinel-2) and enhance or validate such research results with additional ground truth verification products in near-time.

5 References

ADAMCZYK, J. & OSBERGER, A., 2015: Red-edge vegetation indices for detecting and assessing disturbances in Norway spruce dominated mountain forests. International Journal of Applied Earth Observation and Geoinformation, **37**, 90-99.

BENGTSSON, H., 2017: matrixStats: Functions that Apply to Rows and Columns of Matrices (and to Vectors). R Package Version 0.52.2.

BREIMAN, L., 2001: Random forests. Machine Learning, **45**(1), 5-32.

DANDOIS, J. P. & ELLIS, E. C., 2013: High spatial resolution three-dimensional mapping of vegetation spectral dynamics using computer vision. Remote Sensing of Environment, **136**, 259-276.

DASH, J. P., WATT, M. S., PEARSE, G. D., HEAPHY, M. & DUNGEY, H. S., 2017: Assessing very high resolution UAV imagery for monitoring forest health during a simulated disease outbreak. ISPRS Journal of Photogrammetry and Remote Sensing, **131**, 1-14.

DEMPEWOLF, J., NAGOL, J., HEIN, S., THIEL, C. & ZIMMERMANN, R., 2017: Measurement of within-season tree height growth in a mixed forest stand using UAV imagery. Forests, **8**(7), 231.

EINZMANN, K., IMMITZER, M., BÖCK, S., BAUER, O., SCHMITT, A. & ATZBERGER, C., 2017: Windthrow detection in european forests with very high-resolution optical data. Forests, **8**(1), 21.

FACCOLI, M., 2009: Effect of Weather on Ips typographus (Coleoptera Curculionidae) Phenology, Voltinism, and Associated Spruce Mortality in the Southeastern Alps. Environmental Entomology, **38**(2), 307-316.

FAHSE, L. & HEURICH, M., 2011: Simulation and analysis of outbreaks of bark beetle infestations and their management at the stand level. Ecological Modelling, **222**(11), 1833-1846.

FASSNACHT, F. E., LATIFI, H., STEREŃCZAK, K., MODZELEWSKA, A., LEFSKY, M., WASER, L. T., STRAUB, C. & GHOSH, A., 2016: Review of studies on tree species classification from remotely sensed data. Remote Sensing of Environment, **186**, 64-87.

FENG, Q., LIU, J. & GONG, J., 2015: UAV Remote sensing for urban vegetation mapping using random forest and texture analysis. Remote Sensing, **7**(1), 1074-1094.

FRANKLIN, S. E. & AHMED, O. S., 2017: Deciduous tree species classification using object-based analysis and machine learning with unmanned aerial vehicle multispectral data. International Journal of Remote Sensing, **39**(15-16), 5236-5245.

FRANKLIN, S. E., AHMED, O. S. & WILLIAMS, G., 2017: Northern Conifer Forest Species Classification Using Multispectral Data Acquired from an Unmanned Aerial Vehicle. Photogrammetric Engineering & Remote Sensing, **83**(7), 501-507.

GITELSON, A. A., GRITZ, Y. & MERZLYAK, M. N., 2003: Relationships between leaf chlorophyll content and spectral reflectance and algorithms for non-destructive chlorophyll assessment in higher plant leaves. Journal of Plant Physiology, **160**(3), 271-282.

GOODBODY, T. R. H., COOPS, N. C., MARSHALL, P. L., TOMPALSKI, P. & CRAWFORD, P., 2017: Unmanned aerial systems for precision forest inventory purposes: A review and case study. The Forestry Chronicle, **93**(01), 71-81.

HALMSCHLAGER, E. & KIRISITS, T., 2008: First report of the ash dieback pathogen Chalara fraxinea on Fraxinus excelsior in Austria. Plant Pathology, **57**(6), 1177.

HIJMANS, R. J., 2017: raster: Geographic data analysis and modeling. R Package Version 2.6-7.

IMMITZER, M. & ATZBERGER, C., 2014: Early Detection of Bark Beetle Infestation in Norway Spruce (Picea abies, L.) using WorldView-2 Data. Photogrammetrie Fernerkundung Geoinformation, (5), 351-367.

IMMITZER, M., ATZBERGER, C. & KOUKAL, T., 2012: Tree species classification with Random forest using very high spatial resolution 8-band worldView-2 satellite data. Remote Sensing, **4**(9), 2661-2693.

IMMITZER, M., BÖCK, S., EINZMANN, K., VUOLO, F., PINNEL, N., WALLNER, A. & ATZBERGER, C., 2018: Fractional cover mapping of spruce and pine at 1 ha resolution combining very high and medium spatial resolution satellite imagery. Remote Sensing of Environment, **204**, 690-703.

IMMITZER, M., STEPPER, C., BÖCK, S., STRAUB, C. & ATZBERGER, C., 2016a: Use of WorldView-2 stereo imagery and National Forest Inventory data for wall-to-wall mapping of growing stock. Forest Ecology and Management, **359**, 232-246.

IMMITZER, M., VUOLO, F. & ATZBERGER, C., 2016b: First experience with Sentinel-2 data for crop and tree species classifications in central Europe. Remote Sensing, **8**(3), 166.

JONES, H. G. & VAUGHAN, R. A., 2010: Remote sensing of vegetation: principles, techniques, and applications. Oxford University Press.

KIRISITS, T. & FREINSCHLAG, C., 2012: Ash dieback caused by Hymenoscyphus pseudoalbidus in a seed plantation of Fraxinus excelsior in Austria. Journal of Agricultural Extension and Rural Development, **4**(9), 184-191.

KRAUSE, S., HARTMANN, F., MUND, J.-P., 2016: UAV Workflow Optimization for the Acquisition of High Quality Photogrammetric Point Clouds in Forestry. GI_Forum 2016, Vol.1 Page: 72-84

KUHN, M., WING, J., WESTON, S., WILLIAMS, A., KEEFER, C., ENGELHARDT, A., COOPER, T., MAYER, Z., KENKEL, B., TEAM, R. C., BENESTY, M., LESCARBEAU, R., ZIEM, A., SCRUCCA, L., TANG, Y., CANDAN, C. & HUNT, T., 2017: caret: Classification and Regression Training. R Package Version 6.0-78.

LAUSCH, A., HEURICH, M., GORDALLA, D., DOBNER, H. J., GWILLYM-MARGIANTO, S. & SALBACH, C., 2013: Forecasting potential bark beetle outbreaks based on spruce forest vitality using hyperspectral remote-sensing techniques at different scales. Forest Ecology and Management, **308**, 76-89.

LEHMANN, J. R. K., NIEBERDING, F., PRINZ, T. & KNOTH, C., 2015: Analysis of unmanned aerial system-based CIR images in forestry-a new perspective to monitor pest infestation levels. Forests, **6**(3), 594-612.

LIAW, A. & WIENER, M., 2002: Classification and Regression by randomForest. R News, **2**(3), 18-22.

LILLESAND, T., KIEFER, R. W. & CHIPMAN, J., 2014: Remote sensing and image interpretation. John Wiley & Sons.

LINDNER, M., MAROSCHEK, M., NETHERER, S., KREMER, A., BARBATI, A., GARCIA-GONZALO, J., SEIDL, R., DELZON, S., CORONA, P., KOLSTRÖM, M., LEXER, M. J. & MARCHETTI, M., 2010: Climate change impacts, adaptive capacity, and vulnerability of European forest ecosystems. Forest Ecology and Management, **259**(4), 698-709.

LISEIN, J., MICHEZ, A., CLAESSENS, H. & LEJEUNE, P., 2015: Discrimination of deciduous tree species from time series of unmanned aerial system imagery. PLoS ONE, **10**(11), e0141006.

MASAITIS, G., MOZGERIS, G. & AUGUSTAITIS, A., 2013: Spectral reflectance properties of healthy and stressed coniferous trees. IForest, **6**, 30.

MICHEL, J., YOUSSEFI, D. & GRIZONNET, M., 2015: Stable mean-shift algorithm and its application to the segmentation of arbitrarily large remote sensing images. IEEE Transactions on Geoscience and Remote Sensing, **53**(2), 952-964.

MICHEZ, A., PIÉGAY, H., LISEIN, J., CLAESSENS, H. & LEJEUNE, P., 2016: Classification of riparian forest species and health condition using multi-temporal and hyperspatial imagery from unmanned aerial system. Environmental Monitoring and Assessment, **188**(3), 1-19.

MOHAN, M., SILVA, C. A., KLAUBERG, C., JAT, P., CATTS, G., CARDIL, A., HUDAK, A. T. & DIA, M., 2017: Individual tree detection from unmanned aerial vehicle (UAV) derived canopy height model in an open canopy mixed conifer forest. Forests, **8**(9), 340.

NÄSI, R., HONKAVAARA, E., LYYTIKÄINEN-SAARENMAA, P., BLOMQVIST, M., LITKEY, P., HAKALA, T., VILJANEN, N., KANTOLA, T., TANHUANPÄÄ, T. & HOLOPAINEN, M., 2015: Using UAV-based photogrammetry and hyperspectral imaging for mapping bark beetle damage at tree-level. Remote Sensing, **7**(11), 15467-15493.

NEVALAINEN, O., HONKAVAARA, E., TUOMINEN, S., VILJANEN, N., HAKALA, T., YU, X., HYYPPÄ, J., SAARI, H., PÖLÖNEN, I., IMAI, N. N. & TOMMASELLI, A. M. G., 2017: Individual tree detection and classification with UAV-Based photogrammetric point clouds and hyperspectral imaging. Remote Sensing, **9**(3), 185.

NG, W. T., MERONI, M., IMMITZER, M., BÖCK, S., LEONARDI, U., REMBOLD, F., GADAIN, H. & ATZBERGER, C., 2016: Mapping Prosopis spp. with Landsat 8 data in arid environments: Evaluating effectiveness of different methods and temporal imagery selection for Hargeisa, Somaliland. International Journal of Applied Earth Observation and Geoinformation, **53**, 76-89.

NG, W. T., RIMA, P., EINZMANN, K., IMMITZER, M., ATZBERGER, C. & ECKERT, S., 2017: Assessing the potential of sentinel-2 and pléiades data for the detection of prosopis and vachellia spp. In Kenya. Remote Sensing, **9**(1), 74.

OLLINGER, S. V., 2011: Sources of variability in canopy reflectance and the convergent properties of plants. New Phytologist. Wiley/Blackwell (10.1111).

PROVINCIAL GOVERNMENT OF LOWER AUSTRIA, 2015: Naturschutzkonzept Niederösterreich. St. Pölten.

R CORE TEAM, 2017: R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing. Vienna, Austria.

RSTUDIO TEAM, 2016: RStudio: Integrated Development for R. Boston, MA: RStudio Inc.

SCHULTZ, B., IMMITZER, M., FORMAGGIO, A. R., SANCHES, I. D. A., LUIZ, A. J. B. & ATZBERGER, C., 2015: Self-guided segmentation and classification of multi-temporal Landsat 8 images for crop type mapping in Southeastern Brazil. Remote Sensing, **7**(11), 14482-14508.

TOMAŠTÍK, J., MOKROŠ, M., SALOŠ, S., CHUDÝ, F. & TUNÁK, D., 2017: Accuracy of photogrammetric UAV-based point clouds under conditions of partially-open forest canopy. Forests, **8**(5), 151.

TORRESAN, C., BERTON, A., CAROTENUTO, F., DI, S. F., GIOLI, B., MATESE, A., MIGLIETTA, F., ZALDEI, A., WALLACE, L., TORRESAN, C., BERTON, A., CAROTENUTO, F., DI, S. F., GIOLI, B., MATESE, A., MIGLIETTA, F., VAGNOLI, C. & CAROTENUTO, F., 2016: Forestry applications of UAVs in Europe : a review Forestry applications of UAVs in Europe : a review. International Journal of Remote Sensing, 1-21.

TOSCANI, P., IMMITZER, M. & ATZBERGER, C., 2013: Wavelet-based texture measures for object-based classification of aerial images. Photogrammetrie - Fernerkundung - Geoinformation, **2013**(2), 105-121.

WANG, X., WANG, M., WANG, S. & WU, Y., 2015: Extraction of vegetation information from visible unmanned aerial vehicle images. Nongye Gongcheng Xuebao/Transactions of the Chinese Society of Agricultural Engineering, **31**(5), 152-159.

WASER, L. T., KÜCHLER, M., JÜTTE, K. & STAMPFER, T., 2014: Evaluating the potential of worldview-2 data to classify tree species and different levels of ash mortality. Remote Sensing, **6**(5), 4515-4545.

XUE, J. & SU, B., 2017: Significant remote sensing vegetation indices: A review of developments and applications. Journal of Sensors. Hindawi.

ZAMG, 2018: Klimanormalwerte Österreich 1981−2010. Wien.