UAV imagery based tree species classification in the Marburg OpenForest

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Abstract

The monitoring of forests environments is of crucial importance since they serve as natural habitats and constitute a main source of biological diversity on the planet. Yet, it is very costly and labor intensive to monitor forests by traditional means and classical remote sensing technologies restrict the analysis to the regional level. To overcome these challenges there have been several attempts to use UAV-borne imagery in forest monitoring. By the use of drones images can be obtained at low cost and can be associated with both, high spatial and temporal resolution. This enables scientists and practitioners to comprehensively monitor forest environments. Tree species identification is primary interest, since the identification of species allows to draw conclusions about the structure and biodiversity in given areas of a forest. When using simple RGB images, species classification still remains a challenge. In this paper we present our results of an experiment exploring the influence of spatial resolution of RGB imagery, artificially derived vegetation indices as well as seasonal parameters on the accuracy of tree species classification within the Marburg OpenForest. We used a resolution of 5 cm, 10 cm, 15 cm, and 25 cm in a forward-feature-selection based on the Random Forest classification algorithm. Additionally we tested the obtained accuracy when only mono-temporal or multi-temporal variables are included as well as both types of variables. Our results show that . . .

Contents

1 Introduction

Forests environments provide valuable services to the human well being as well as supporting services to the function of ecosystems. Additionally, they count to the main biodiversity hotspots on earth (Brockerhoff et al., 2017). However, the most recent Global Forest Resource Assessment of the FAO states, that the global forest area shrinked between 1990 and 2015 from 31.6% of the global land cover to 30.6%, or in other numbers from 4,128 Mio. ha to 3,999 Mio. ha - a decrease of 3.1% (Food and Agriculture Organsiation of the United Nations, 2015). Simultaneously, the percentage of planted trees increased by over 105 Mio. ha, reducing the share of natural forest areas. Over the last decades, we can find growing scholar interests on ecosystem services and functions which are sustained by forests, mainly the habitat provision for endangered or native species, the provision of material goods such as wood biomass, soil formation and composition, as well as climatic regulation functions, such as carbon sequestration (Brockerhoff et al., 2017). One of the main critical variables in assessing the quality of forest environments, their biodiversity, and their structural attributes is the tree species, either on the individual tree level or the dominating species for coarser areas of interest.

Identifying tree species, however, on an operative scale for larger areas, remains a challenge. Recently, different remote sensing approaches proved that tree species identification from above the earth's surface is feasible, but there still remain significant trade-offs between the costs, computational demand and spatial-temporal resolution of remotely sensed imagery. Some studies have used satellite imagery which most frequently also include information in the infrared spectrum (Elatawneh et al., 2013; Grabska et al., 2019; Persson et al., 2018; Ulsig et al., 2017; Zhang et al., 2003) but generally shows a relatively low spatial resolution limiting the analysis to a level of stand rather than individuals. Additionally, depended on the platform's orbit and current weather conditions, the temporal resolution may vary significantly and is not completely planable.

One technology to partly overcome these restrictions is the use of Radio Detection And Ranging (RADAR) sensors which show a lower dependency of data quality to the presence of clouds and fog. Recently, multi-temporal data from Sentinel-1 has been used in conjunction with spectral data to not only improve the species classification accuracy but also to retrieve additional parameters important to forest monitoring such as forest type, stand density, annual phenology, and biomass production among others (Dostálová et al., 2018; Frison et al., 2018; Mngadi et al., 2019; Niculescu et al., 2018). However promising these advances, the analysis are most commonly restricted to regional analysis of forest structures. On a more localized level, high resolution satellite data is either not available or associated with very high costs. With the rapid development of unmanned aerial vehicles (UAV) during the last years and a significant decrease in price for this technology, new approaches to monitor forest structures on a very local level have recently emerged (Yao et al., 2019).

UAVs serve as an aerial platform of different kind of sensors which can range from LidAR (Fricker et al., 2019), hyper- and multi spectral sensors (Berra et al., 2019; Marques et al., 2019) as well as simple RGB cameras (Natesan et al., 2019). A broad methodology to obtain species information for single tree individuals has been developed integrating the calculation of various vegetation indices from mono- and multi-temporal imagery and the use of machine learning models to derieve a relationship between the measured variables and the tree species (Berra et al., 2019, 2016; Fricker et al., 2019; Klosterman et al., 2018; Klosterman and Richardson, 2017; Natesan et al., 2019). Berra et al. (2016) used the Green Chromatic Coordinate to monitor the Start-of-Season for four different tree species in decidous woodland suggesting that UAV imagery can contribute to investiage the phenologocial statu of individuak trees. Klosterman and Richardson (2017) were able to estimate phenological status on the leaf-level based on the calculation of the green and red chromatic coordinate (GCC and RCC) during spring and autumn to budburst and leaf expansion as well as leaf senescence. Natesan et al. (2019) used Residual Neural Networks to classify three different tree species based on RGB imagery obtained over the course of three years and achived a classification accuracy of about 80%, and an accuracy of 51% when only the data of single years was used. Fricker et al. (2019) used hyperspectral images obtained by a UAV and a Convolutional Neural Network to classify tree species. They also underwent an experiment which only included RGB data. The hyperspectral data achieved an F-score of 0.87, while the RGB data achieved a score of 0.64 in a dominantly coniferous forest.

Additionally, the development of structure-from-motion algorithms to get 3D information from 2D RGB imagery taken from slightly different angles have enriched the analysis of forest structures from low-cost sensors (Brieger et al., 2019; Krause et al., 2019; Nevalainen et al., 2017; Onishi and Ise, 2018; Sothe et al., 2019; Yan et al., 2018). Nevalainen et al. (2017) used RGB images and an automated matching technique to obtain point clouds at a 5cm resoultion. Coupled with hyperspectral imagery this allowed the tree species classification to an accuracy at 95%. Yan et al. (2018) compared thier approach of retrieving tree crowns from RGB images with crowns delinated from LiDAR data and report an accuracy at about 90%. Krause et al. (2019) were able to retrive individual tree height based on a photogrammetric point-cloud with an RMSE at about 2-3 %. Brieger et al. (2019) used RGB derived point clouds at different study sites in Siberia and achived an accuracy of 67.1% in delinating individual tree crowns and an RMSE of 18.46% for tree height. Sothe et al. (2019) used hyperspectral images for tree delination and classification in subtropical rainforests and achived and Kappa score of 0.7 (overall accuracy of 72.4%) by combining spectral raw data, indices as well as structural parameters in the classification process using a support-vector machine.

So far, in our best knowledge, there has not been any attempts reported to the scientific community to structurally investigate the impact of decreasing spatial resolution on the classification accuracy as well as the impact of the integration of seasonal parameters derived from multiple mono-temporal observations. Here, we strictly limit our analysis to the investigation of these two thematic blocs and deliberatly exclude other factors such as structural variables obtained from point clouds. We solely focus on the analysis of the dynamic in predictive potential of RGB derived mono- and multi-temporal variables to model tree species with changing spatial resoulution.

2 Data and Method

2.1 Study Area

2.2 Pre-Process

2.2.1 UAV orthoimages

Table 1: Dates of the UAV overpasses.

Dates
2019-04-29
2019-05-03
2019-05-10
2019-05-16
2019-06-05
2019-06-20

In this project, AgisoftPhotoScan (???) in the version (???) was used to process the UAV imagery. Agisoft Photoscan Professional is anaffordable 3D reconstruction software from the Russian company Agisoft LLC (Agisoft, 2018) for the generation of dense point clouds and photogrammetric products such as orthorectified mosaics and DSM derived from images. Photoscan has the advantage to provide a simple workflow, from performing bundle block adjustment to calibrate the camera and orientate images after automatic tie point measurements, geo-referencing by measuring ground control points, concluding with the computation of a dense point cloud and requested final products (Mayer et al. 2018 ???? Mendely hinzuf?gen). The Airborne system (???Drohnenname) was used to acquire the UAV imagery using a commercial goPro (???Model + Objektiv. In (??? Anzahl flights) flight campaigns with a flight altitude of (40 meters???), (???Anzahlfotos) photos were acquired. The internal GPS of the GoPro was used for geotagging the images. A post referencing enabled a better processing of the images in SFM software (Version???) and more accurate orthophotos without manual referencing in Photoscan. Photo Alignment is a process in PS for image matching and bundle block adjustment in an arbitrary system. It generates a sparse point cloud as well as the interior and exterior orientation parameters of all images in that system, including systematic error compensation such as non-linear lens distortions. Prior to the adjustment, the tie points are automatically measured by detecting and matching features in overlapping images resulting in a sparse point cloud (Mayer et al. 2018??? Mendely hinzuf?gen).The settings in this project were chosen as follows: - General: Accuracy: Medium;

Generec preselection: yes; Reference preselection: yes - Advances: Key Piont limit: 40000; Tie point limit: 4000; apply mask: no; Adaptive camera model fitting: yes

Sparse cloud filtering was performed under the following settings: -gradual Selection: reprojection error: 0.26; reconstruction uncertainty: 189.461; projection accuracy:12.4621; reconstruction uncertainty:6.72951; reprojectionerror:0.122199

Based on the information of the point cloud (Sparse Cloud, Dense Cloudetc . . .) PhotoScan can construct a polygon model (Mesh) (Agisoft 2018??? Mendeley hinzuf?gen) In this Project the Mesh was build by following setting: - General: surface type: Height field (2.5D); source data: sparse cloud; face count: medium - advanced: Interpolation: enabled; Point classes: all; calculate vertex colors

The different pixel values from different photos are combined by the Mosaic type in the final texture. Mosiac type implies a two-step approach. Low frequency components are blended for overlapping images to avoid seam line problems. The high-frequency component, on the other hand, which is responsible for the image details, is only captured from a single image.

In total we worked on 6 images which were obtained between the end of April to the end of June. In the mitlatitudes of central Europe these are the months of vegetational peak of mixed forests. We calculated a selection of RGB-based vegetational indices for each of the images as well as seasonal statistics which describe the development of these indices in the course of the vegetation period.

- UAV orthoimages, AgiSoft (how-to), flight height
- pre-process: crop to AOI, spatial aggregations different resolutions, indices, season parameters
- tree shape: differential GPS points, >= 40cm DBH, 2m buffer, squares -> species
- RF model, 5-fold cross validation, training vs. testing, kappa & accuracy,
- plots predictors (all, indices, seasons) vs. resolutions

2.2.2 Auxiliary data

2.3 Random Forest Classification and Evaluation

```
## OGR data source with driver: ESRI Shapefile
## Source: "/mnt/SSD/phenology/data/trees_buffer.shp", layer: "trees_buffer"
## with 161 features
## It has 13 fields
```

3 Results

4 Discussion

5 Conclusion

6 Results

References

Berra, E.F., Gaulton, R., Barr, S., 2019. Assessing spring phenology of a temperate woodland: A multiscale comparison of ground, unmanned aerial vehicle and Landsat satellite observations. Remote Sensing of Environment 223, 229–242. https://doi.org/10.1016/j.rse.2019.01.010

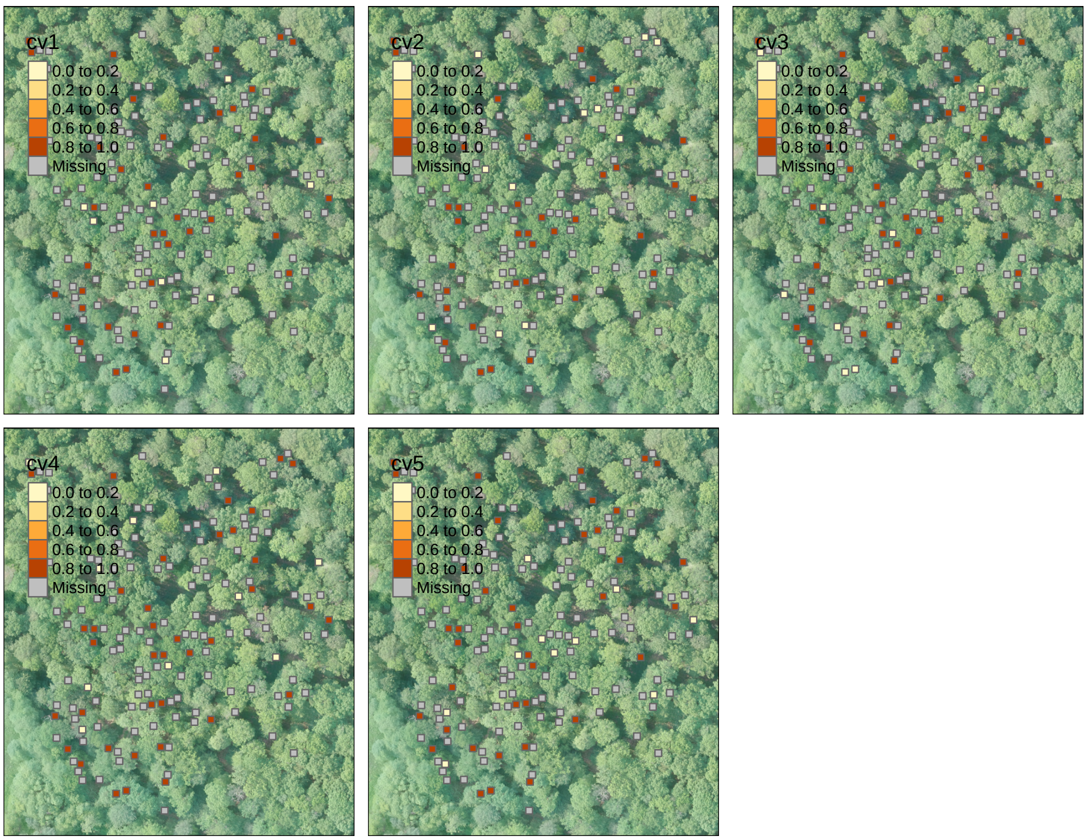

Figure 1: Overview of the training and validation trees of the five-fold cross-validation.

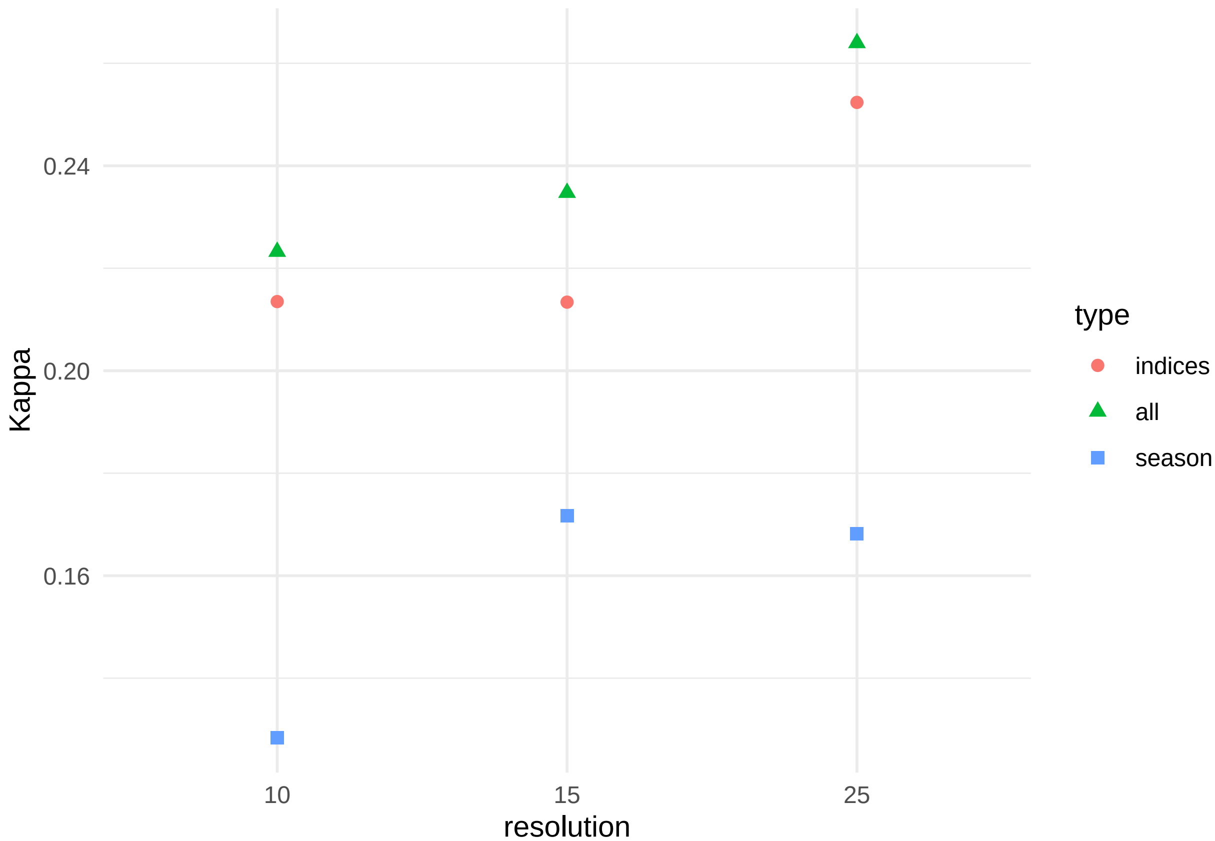

Figure 2: Kappa scores of the random fores models based varying pixel sizes and predictor variables (red - mono-temporal indices, blue - seasonal indices, green - mono-temporal and seasonal indices)

Berra, E.F., Gaulton, R., Barr, S., 2016. Use of a digital camera onboard a UAV to monitor spring phenology at individual tree level, in: 2016 Ieee International Geoscience and Remote Sensing Symposium (Igarss). pp. 3496–3499. https://doi.org/10.1109/IGARSS.2016.7729904

Brieger, F., Herzschuh, U., Pestryakova, L.A., Bookhagen, B., Zakharov, E.S., Kruse, S., 2019. Advances in the derivation of Northeast Siberian forest metrics using high-resolution UAV-based photogrammetric point clouds. Remote Sensing 11, 1447. https://doi.org/10.3390/rs11121447

Brockerhoff, E.G., Barbaro, L., Castagneyrol, B., Forrester, D.I., Gardiner, B., González-Olabarria, J.R., Lyver, P.O., Meurisse, N., Oxbrough, A., Taki, H., Thompson, I.D., Plas, F. van der, Jactel, H., 2017. Forest biodiversity, ecosystem functioning and the provision of ecosystem services. Biodiversity and Conservation 26, 3005–3035. https://doi.org/10.1007/s10531-017-1453-2

Dostálová, A., Wagner, W., Milenković, M., Hollaus, M., 2018. Annual seasonality in Sentinel-1 signal for forest mapping and forest type classification. International Journal of Remote Sensing 39, 7738–7760. https://doi.org/10.1080/01431161.2018.1479788

Elatawneh, A., Rappl, A., Rehush, N., Schneider, T., Knoke, T., 2013. Forest tree species communities identification using multi phenological stages RapidEye data : case study in the forest of Freising. 5. RESA Workshop 4/2013 1–10.

Food and Agriculture Organsiation of the United Nations, 2015. Global Forest Resources Assessment 2015. https://doi.org/10.1002/2014GB005021

Fricker, G.A., Ventura, J.D., Wolf, J.A., North, M.P., Davis, F.W., Franklin, J., 2019. A Convolutional Neural Network Classifier Identifies Tree Species in Mixed-Conifer Forest from Hyperspectral Imagery. Remote Sensing 11, 2326. https://doi.org/10.3390/rs11192326

Frison, P.L., Fruneau, B., Kmiha, S., Soudani, K., Dufrêne, E., Le Toan, T., Koleck, T., Villard, L., Mougin, E., Rudant, J.P., 2018. Potential of Sentinel-1 data for monitoring temperate mixed forest phenology. https://doi.org/10.3390/rs10122049

Grabska, E., Hostert, P., Pflugmacher, D., Ostapowicz, K., 2019. Forest stand species mapping using the sentinel-2 time series. Remote Sensing 11, 1–24. https://doi.org/10.3390/rs11101197

Klosterman, S., Melaas, E., Wang, J., Martinez, A., Frederick, S., O'Keefe, J., Orwig, D.A., Wang, Z., Sun, Q., Schaaf, C., Friedl, M., Richardson, A.D., 2018. Fine-scale perspectives on landscape phenology from unmanned aerial vehicle (UAV) photography. Agricultural and Forest Meteorology 248, 397–407. https://doi.org/10.1016/j.agrformet.2017.10.015

Klosterman, S., Richardson, A.D., 2017. Observing spring and fall phenology in a deciduous forest with aerial drone imagery. Sensors (Switzerland) 17. https://doi.org/10.3390/s17122852

Krause, S., Sanders, T.G., Mund, J.P., Greve, K., 2019. UAV-based photogrammetric tree height measurement for intensive forest monitoring. Remote Sensing 11, 758. https://doi.org/10.3390/rs11070758

Marques, P., Pádua, L., Adão, T., Hruška, J., Peres, E., Sousa, A., Sousa, J.J., 2019. UAV-based automatic detection and monitoring of chestnut trees. Remote Sensing 11, 855. https://doi.org/10.3390/RS11070855

Mngadi, M., Odindi, J., Peerbhay, K., Mutanga, O., 2019. Examining the effectiveness of Sentinel-1 and 2 imagery for commercial forest species mapping. Geocarto International 0, 1–12. https://doi.org/10.1080/10106049.2019.1585483

Natesan, S., Armenakis, C., Vepakomma, U., 2019. Resnet-based tree species classification using uav images. International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences - ISPRS Archives 42, 475–481. https://doi.org/10.5194/isprs-archives-XLII-2-W13-475-2019

Nevalainen, O., Honkavaara, E., Tuominen, S., Viljanen, N., Hakala, T., Yu, X., Hyyppä, J., Saari, H., Pölönen, I., Imai, N.N., Tommaselli, A.M., 2017. Individual tree detection and classification with UAV-Based photogrammetric point clouds and hyperspectral imaging. Remote Sensing 9. https://doi.org/10.3390/rs9030185

Niculescu, S., Talab Ou Ali, H., Billey, A., 2018. Random forest classification using Sentinel-1 and Sentinel-2 series for vegetation monitoring in the Pays de Brest (France), in:. p. 6. https://doi.org/10.1117/12.2325546

Onishi, M., Ise, T., 2018. Automatic classification of trees using a UAV onboard camera and deep learning.

Persson, M., Lindberg, E., Reese, H., 2018. Tree species classification with multi-temporal Sentinel-2 data. Remote Sensing 10, 1–17. https://doi.org/10.3390/rs10111794

Sothe, C., Dalponte, M., Almeida, C.M. de, Schimalski, M.B., Lima, C.L., Liesenberg, V., Miyoshi, G.T., Tommaselli, A.M.G., 2019. Tree species classification in a highly diverse subtropical forest integrating UAV-based photogrammetric point cloud and hyperspectral data. Remote Sensing 11, 1338. https://doi.org/10.3390/rs11111338

Ulsig, L., Nichol, C.J., Huemmrich, K.F., Landis, D.R., Middleton, E.M., Lyapustin, A.I., Mammarella, I., Levula, J., Porcar-Castell, A., 2017. Detecting inter-annual variations in the phenology of evergreen conifers using long-term MODIS vegetation index time series. Remote Sensing 9. https://doi.org/10.3390/rs9010049

Yan, W., Guan, H., Cao, L., Yu, Y., Gao, S., Lu, J.Y., 2018. An automated hierarchical approach for three-dimensional segmentation of single trees using UAV LiDAR data. Remote Sensing 10, 1999. https://doi.org/10.3390/rs10121999

Yao, H., Qin, R., Chen, X., 2019. Unmanned aerial vehicle for remote sensing applications - A review. https://doi.org/10.3390/rs11121443

Zhang, X., Friedl, M.A., Schaaf, C.B., Strahler, A.H., Hodges, J.C., Gao, F., Reed, B.C., Huete, A., 2003. Monitoring vegetation phenology using MODIS. Remote Sensing of Environment 84, 471–475. https://doi.org/10.1016/S0034-4257(02)00135-9