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Master Physische Geographie WS18/19
Remote Sensing

Philipps Universität Marburg

Introduction

Remote Sensing allows to collect spectral information of the earth surface for vast areas in a time-effective way. This information can be used by environmental sciences to continuously monitor a broad spectrum of parameters characterizing very different ecosystems. One of this parameter maybe the species of individual trees in forest areas. The usefulness of different types of remotely sensed data is primary depended on the specific application the data is going to be used in and the skill-set of the user of the data as well as the available computation power. For every application a balanced way between the means and the aim needs to be found. Here, we investigated the possibility to predict individual tree species based on freely available RGB images of the University Forest Caldern. RGB images are easily accessible and require less developed data management skills than compared to other types of data, e.g. hyper-spectral-data. Yet, RGB images are by far less expensive to obtain especially since the decrease of costs of high-resolution sensors in form of simple digital cameras and the wide-spread availability of user-friendly drones. Therefore, we set out to test a workflow using a Random Forest classifier in order to map tree species.

RGB Indices

Tab.1: Calculated RGB Indices

Index	Name	Formula	Index	Name	Formula
1. VVI	Visual Vegetation Index	(1-(Red-30)/(Red+30))*(1 -(Green-50)/(Green+50))*(1-(Blue-1)/(Blue+1))	7. TGI	Triangulated Greenness Index	-0,5(190(Red-Green)-120(Red-Blue)
2. VARI	Visible Atmospherically Resistant Index	(Green-Red) / (Green+Red-Blue)	8. GLI	Green Leaf Index	(2xGreen – Red – Blue) / (2xGreen + Red + Blue)
3. CIVE	Colour Index of Vegetation	0,441xRed - 0,8116xGreen + 0,385xBlue + 18,787	9. NGRDI	Normalized Green-Red Difference Index	(Green – Red) / (Green + Red)
4. CI	Soil Colour Index	(Red-Green)/(Red+Green)	10. RGRI	Red Green Ratio Index	Red / Green
5. BI	Brightness Index	SQRT((Red² + Green² + Blue²)/3)	11. MGRVI	Modified Green Ratio Vegetation Inex	(Green² - Red²) / (Green² + Red²)
6. SI	Shadow Index	(Red-Blue) / (Red+Blue)	12. ExG	Excess Green	2Green – Red – Blue

Fig. 1: Example of used RGB Indices

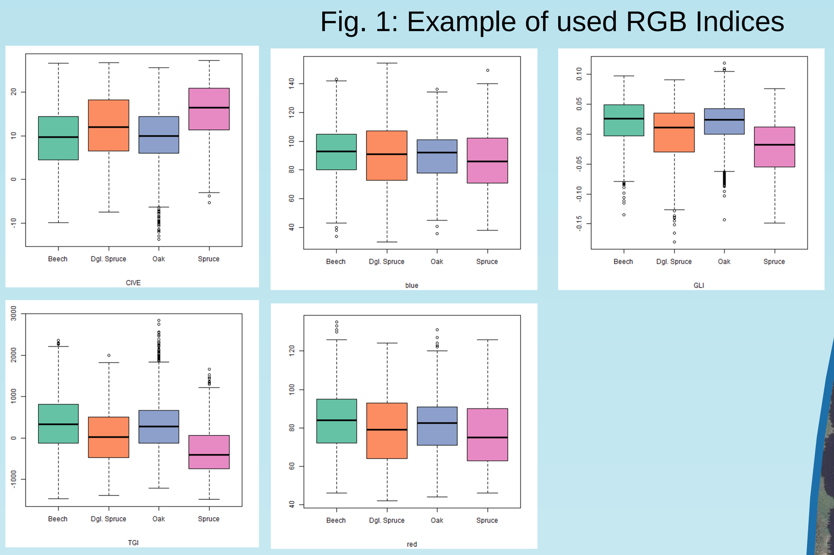
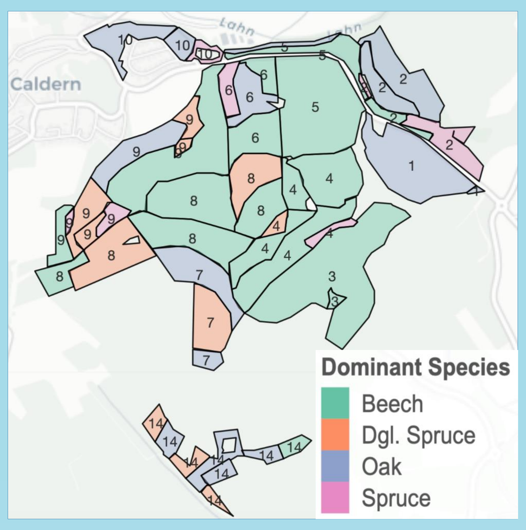
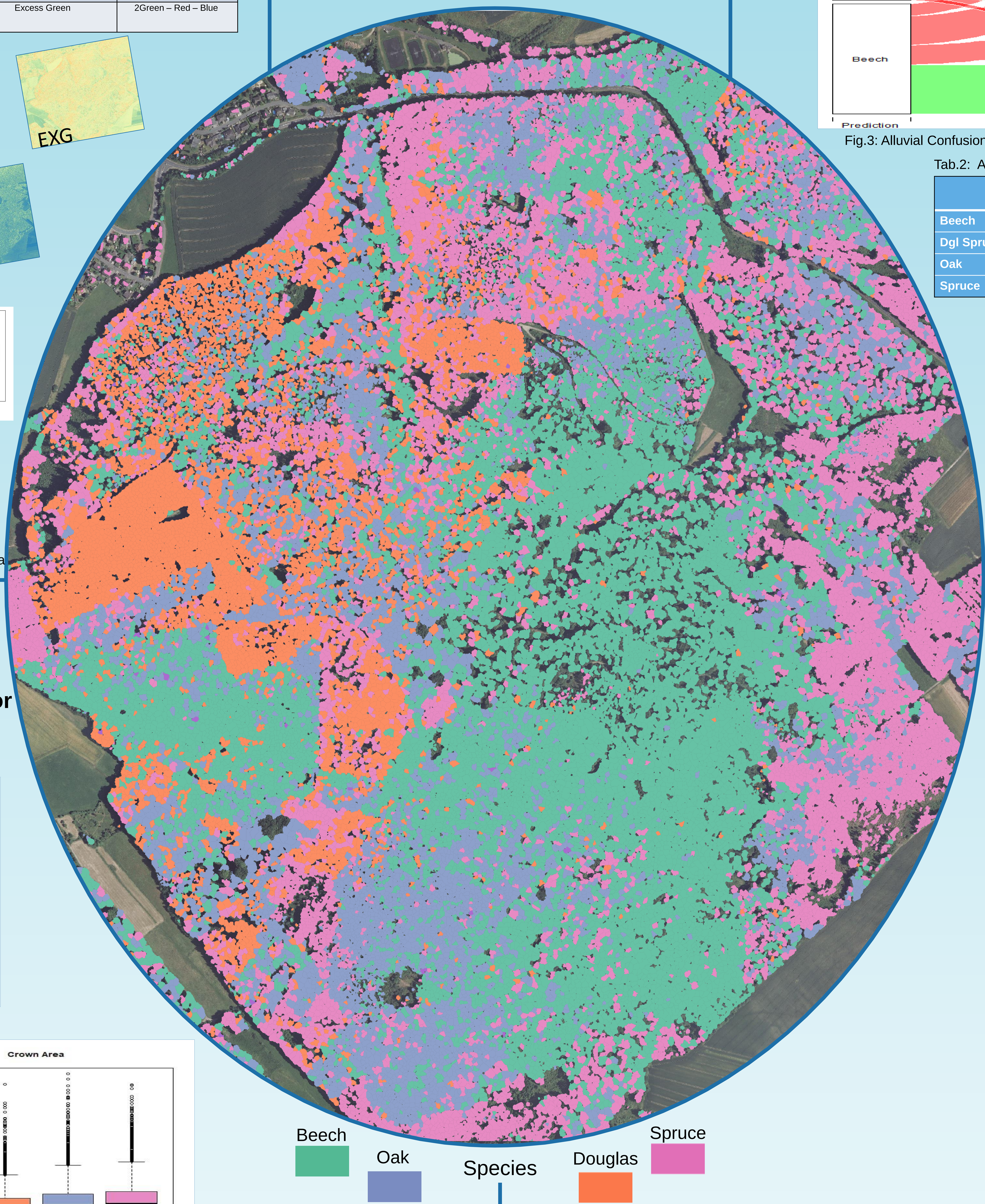


Fig. 2: Distribution of VIs used as predictors in the training data

Area of Interest



Tree Classification Marburg Open Forest



Random Forest Algorithm for Tree Classification

Random Forest constitutes a very common and non-parametric classification algorithm. It is suspected to perform well on multi-class classification problems and a large amount of predictor variables. We implemented a Forward-Feauture-Selection to chose the best predictors for our classification problem.

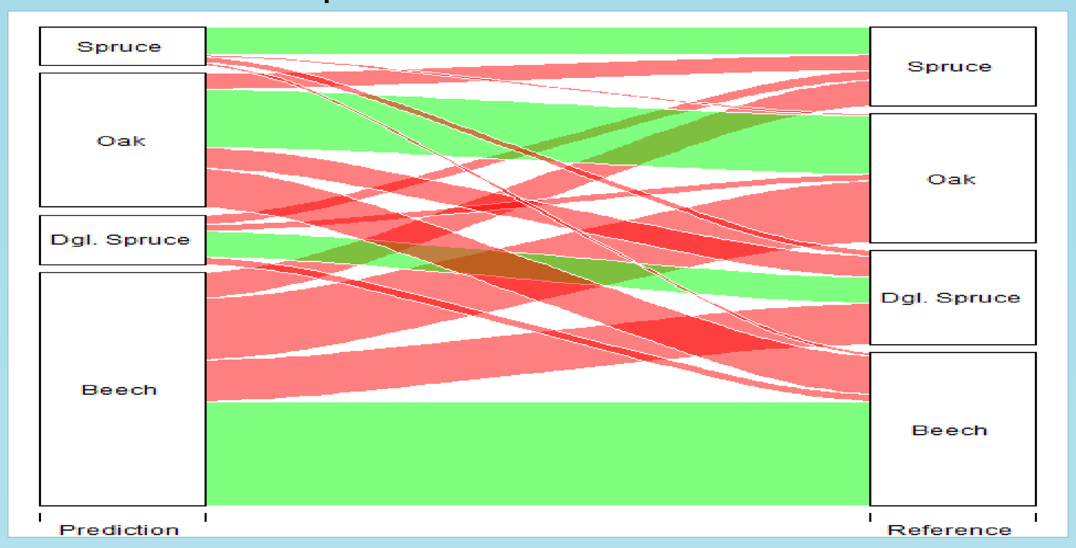


Fig.3: Alluvial Confusion Matrix

Tab.2: Accuracy values for each species

	Sensitivity	Specificity	Pos Pred Value	Neg Pred Value	Balanced Accuracy
Beech	0.47	0.79	0.70	0.58	0.63
Dgl Spruce	0.56	0.84	0.29	0.94	0.70
Oak	0.46	0.79	0.48	0.78	0.63
Spruce	0.73	0.88	0.36	0.97	0.81

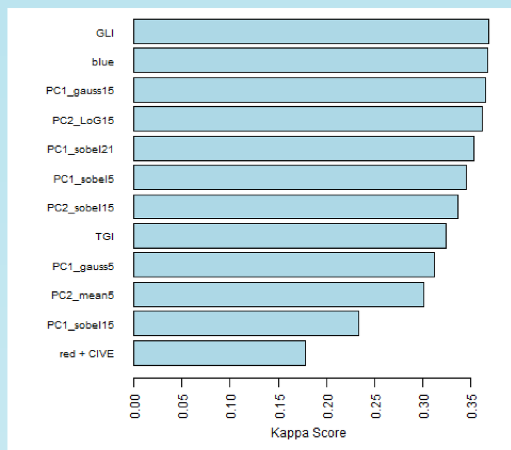


Fig.4 Used predictors for the classification

Interactive Exploration of Geographic Data

We believe that today's **digital possibilities** should be used to allow people to **intuitively interact** with data to generate more useful information. This process needs to be based on a great level of **transparency** about the data and the methods used to generate scientific results. In order to achieve this we decided to create a website that allows users to interact with our results as well as with our code. This brings the double benefit of offering transparency to a possibly broad audience at comparatively **low costs** and therefore enable developers and users to **engage in a dialog** with the researcher who created a workflow to use GIS in a specific problem setting. In order to access our webpage your are invited to scan the QR-Code below, which will lead you to a GitHub-Repository containing our results.

SCAN ME

Statistics Aggregated by Species for Marburg Open Forest (MOF)

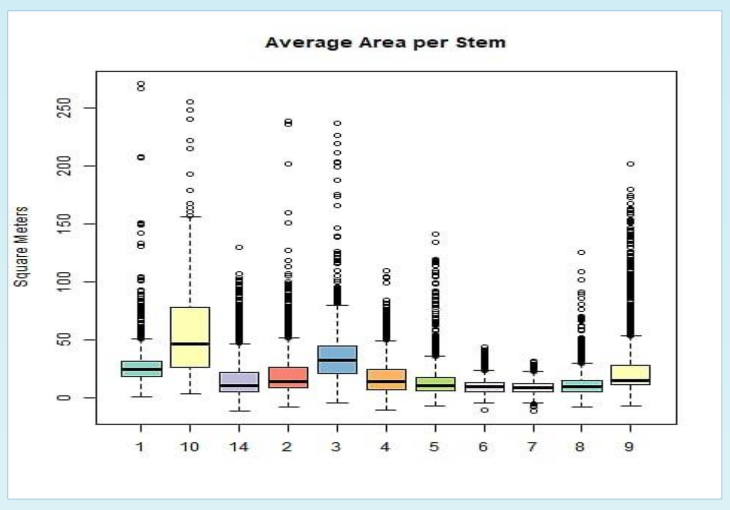


Fig. 5: Average Area per Stem

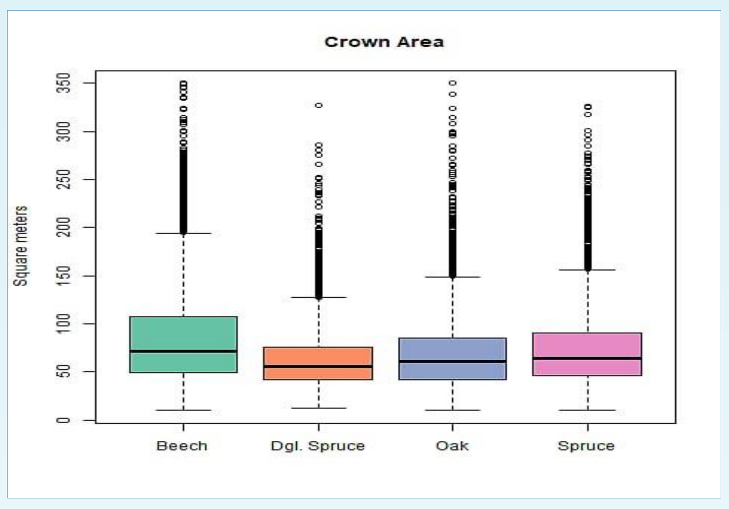


Fig. 6: Crown Area

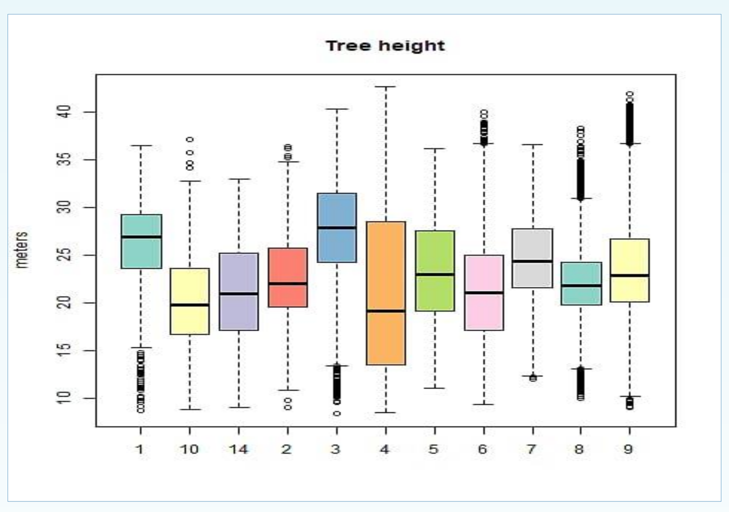


Fig. 7: Tree Height by department

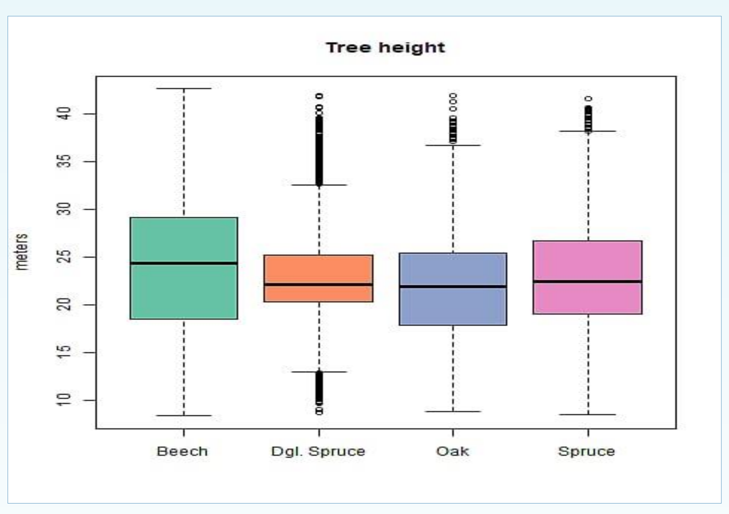


Fig. 8: Tree Height by species

Discussion

- Kappa value of **0.36** represents only a fair level of agreement
- Principal Component represents valuable method to conflate RGB based information of various indices
- Spatial filter, especially the sobel filter, helps to identify tree species
- a balanced training dataset might not result to an area where classes are very unevenly distributed
- To obtain spatial information on tree species form the individual level up to large scale patterns based on RGB images is generally possible, but to obtain high quality results a through handling of the data and calibration of the model is mandatory

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