EUFAR Training Course
Airborne Remote Sensing for Monitoring Essential Biodiversity Variables in Forest Ecosystems (RS4forestEBV)
Bavarian Forest National Park and German Aerospace Center, Germany,
3-14 July 2017
Lecture 11: Tree Species Classification
Nicole Pinnel, German Remote Sensing Data Center
Tree species information

Motivation by a wide variety of applications confronting the forest management and conservation sector:

- Resources inventories
- Biodiversity assessment
- Hazard and stress management
- Monitoring invasive species
- Wildlife habitat mapping
- Sustainable forest management
Objective

- General trends in remote sensing studies focusing on tree species classification
- Provide an overview of the current approaches for classifying tree species
- Identify research gaps and future trends for tree species classification using remote sensing data
- Case study: Bavarian Forest National Park
Overview

Descriptive statistics compiled from 116 selected studies focusing on tree species mapping

Overview

Number of species per sensor type.

Descriptive statistics compiled from 116 selected studies focusing on tree species mapping

Challenge

Capture the complex inter- and intra-species spectral variability and the problem of spectral similarity.

→ Additional data needed (LiDAR, Vegetation indices etc.)
Optimal ground sampling density and spatial unit
Ground sampling density and spatial unit

What is the spatial unit on which species information should be obtained?

What is the optimal ground sampling density (pixel size) of a given sensor to derive tree species information?
Spatial resolution and scale

- Complex interplay of radiation with crown tissues (foliage, stems, branches, fruits, lianas and flowers)
- Background signal (stemming from soil, herbaceous vegetation)
- Structural arrangement of foliage (number of layers, clumping and leaf angles) and shadow fractions
- View-illumination geometry
Spatial resolution and scale

What is the optimal pixel size for classifying tree species?

Fassnacht (2015)
Spatial resolution and scale

What is the optimal pixel size for classifying tree species?

Experiences from case studies (II)


Spatial resolution and scale

What is the optimal pixel size for classifying tree species?

Case studies suggest:
Either possibly small pixels (< 0.5 m)
Or: pixels close to the size of an individual crown

BUT: So far the spatial unit was a pixel!

Spatial resolution and scale

What is the optimal spatial unit to obtain species information?

Three obvious approaches:

(I) Pixel
(II) Single-tree objects
(III) Stands or other operational unit

What is the optimal spatial unit to obtain species information?

Advantages of object-based approaches (single tree and stand-level) in case accurate objects can be obtained:

- Meaningful units (practitioners work with it)
- Combination of LiDAR and Hyperspectral becomes more powerful:
  - Normalization of spectra (sunlit parts of the crowns)
  - Majority voting approaches
  - Single-tree based geometric information (crown-base height, canopy transects, crown volume, ...)
  - Density information from LiDAR + spectral information from satellites

Spatial resolution and scale

What is the optimal spatial unit to obtain species information?

Challenges of object-based approaches (single tree and stand-level):

- The quality of the results largely depends on the delineation success

- Classifications on stand-level-objects have to consider that differing forest densities may lead to very distinct reflectance signals for the identical species composition

Spatial resolution and scale

- An argument for small pixel sizes is that the increased spectral variability can be methodically addressed by applying object-based approaches.
- The distribution of spectral signatures of the pixels within a crown object could vary amongst species and therefore contain relevant information.
- Optimal spatial resolution will also depend on the applied methods and the forest types under investigation.

Spectral resolution and range
Spectral resolution and range

- Do we need to cover the full VIS-SWIR region?

- How narrow should the bands be?

- How to deal with spectral resolution in an operational approach?
Spectral resolution and range

Capture the complex inter- and intra-species spectral variability and the problem of spectral similarity.

Mean spectral signatures of the 13 tree species

- Sycamore maple (AP)
- European aspen (PT)
- European white birch (BP)
- European beech (FS)
- Douglas fir (PM)
- European alder (AG)
- European ash (FE)
- Norway spruce (PA)
- Scots pine (PS)
- European larch (LD)
- European silver fir (AA)
- European rowan (SA)
- Sallow (SC)
Spectral resolution and range

HySpex VNIR forest type

WV-2 forest type

A. Reichmuth (2013)
Spectral resolution and range

Species–related traits measured by RS

- Important wavelength regions
- Texture information
- Phenology
- Ecotypes, site condition and leaf age

Species related traits

Important wavelength regions

Species related traits

http://speclab.cr.usgs.gov/PAPERS.refl-mrs/giff/300dpi/fig3a3.gif
Species related traits

Crown Texture

• Mainly related to crown-internal shadows, foliage properties (size, density, reflectivity) and branching

• On coarser scales, crown size, crown closure, crown shape, stand density and forest type (broadleaved, coniferous) are the main driver for texture in passive optical imagery.

• Owing to the multiscale perspective of texture, the optimum window size varies for example with the crown diameter of a specific tree.

Species related traits

Phenology

- Coloring of leaves due to senescence (faster decomposition of chlorophyll pigments in comparison to Anthocyanins and Carotenoids)
- Green colours of fresh leaves and needles (flowering events)
- Species specific knowledge is preferable over forest phenology
- Image acquisition aligned with phenological cycle is desirable

Spectral resolution and range

The diagram illustrates the spectral response of leaf pigments, cell structure, and water content. The x-axis represents wavelength in microns, ranging from 0.4 to 2.4. The y-axis shows the percentage reflectance relative to halon. The graph highlights different conditions:

- Chlorophyll-carotenoid-absorption
- H₂O-absorption

Different lines indicate various conditions:

- Healthy (green)
- Stressed
- Dry (brown)

The diagram provides insights into how spectral resolution and range affect these different conditions.
Species related traits

Ecotypes, site condition, leaf age

- Reflectance differences between the same species at different locations
- Mostly related to variable site conditions (at larger geographic extents)
Species related traits

LiDAR

- Mainly structure information
- Architecture of crowns, branching, and foliage
- The intensity of backscattered signal is connected to foliage type, leaf type, leaf orientation, leaf dumping and foliage density

Mid-infrared and thermal-infrared sensors

Spectral resolution and range

Do we need to cover the full VIS-SWIR region?

Based on the studies so far: Yes!

But: some regions are more important than others

→ optimize processing speed?

Spectral resolution and range

How narrow should the bands be?

Question is connected to processing speed (number of predictors)

Radiometric noise vs. ability to capture subtle absorption features

Hardly any systematic investigation available so far

Results for SAM classifier applied to noise-reduced image (MNF)

Spectral resolution and range

How narrow should the bands be?

“Gut feeling / hypothesis”:

A sensor with 100-150 narrow bands (VIS-SWIR) should do the job

Having very narrow 400 bands won’t add a lot of useful information in a classification problem (co-linearity)
Methods for tree species classification

Reference data

- Considered classes have to match the research question
- The data should be representative for the site of investigation
- The spatial scale should match the problem under investigation
- The data should acknowledge the underlying assumption of applied methodology (e.g. minimum number of samples per class etc.)
- Observation errors should be known and their impact on the results should be discussed
- Samples should be spatially independent

Methods for tree species classification

Calibration and validation

- Simple data splitting (70% of training, 30% of validation)
- X-fold cross validation (samples are randomly split into x parts (folds) of equal sample size)
- Bootstrap – resampling (n-reference samples get sampled n times with replacement (out of bag validation of random forest (RF))
- Recommendation iterative data splitting approach and an additional completely independent test set as a gold standard for tree species classification studies.

Methods for tree species classification

Feature reduction

Feature extraction methods (MNF, PCA, SVM) selects a subset of the original predictor variables.

Feature selection methods (Stepwise procedures, RF, GA) calculates new predictor variables that typically summarize the content of several original predictors.

Methods for tree species classification

Classification algorithm

Non-parametric machine learning methods (RF, SVM), using mixed sets of input variables (spectral, texture, geometric, indices)

## Methods for tree species classification

<table>
<thead>
<tr>
<th>Classification approach</th>
<th>Advantage</th>
<th>Disadvantage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Discriminant Analysis (linear, quadratical, canonical, stepwise, regularized, penalized)</td>
<td>LDA does not require the tuning of parameters Accepts multiple input variables. Easier interpretation of Between-class differences</td>
<td>Assumes Gaussian distribution of training data Classical discriminant analyses are less sensitive to ill-posed problems and outliers. Noisy results in complex landscapes. Limited ability to deal with multi-collinearity</td>
</tr>
<tr>
<td>Maximum Likelihood</td>
<td>Consistent approach for a variety of estimation Problems Approx. unbiased in presence of larger sample sizes. Many software implementations.</td>
<td>Assumes Gaussian distribution of training data Biased for small samples. Sensitive to the number of input variables</td>
</tr>
<tr>
<td>Random Forest (RF)</td>
<td>No distributional assumption required Less sensitive to the number of input Variables Less sensitive to overfitting</td>
<td>Might overfit in presence of noisy data. Might be biased in case response classes have different number of levels</td>
</tr>
<tr>
<td>SVM</td>
<td>No distributional assumption required. Suitable when incorporating non-remote sensing variables into classification robust to noise and high-dimensional data fast predictions (sparse model due to support vectors). Comparably few training data needed. Possibility to easily access probability values instead of only discrete classes</td>
<td>Optimal design of a multi-class SVM is demanding Comparatively high computational cost (algorithmic complexity) for training Selection of kernel function parameters</td>
</tr>
<tr>
<td>Neural Networks</td>
<td>Able to extract patterns and identify trends from pool of data Implemented by many software packages Suitable to deal with classification problems which are hardly mathematically definable</td>
<td>Difficult to train, since the results are ultimately dependent on the initial parameters Black box-like setup</td>
</tr>
</tbody>
</table>

Methods for tree species classification

- Atmospheric correction
- Anisotropy effects: brightness of an observed object depends on the view illumination geometry (BRDF)
- Data fusion

Case Study

Bavarian Forest National Park

- First National Park in Germany
  - Founded: 1970
  - Enlarged: 1997
- Currently: 24,369 ha
- 22 tree species
Bavarian Forest National Park

Data acquisition 22. & 27.7.2013
1.6m / 3.2m pixel resolution
Bavarian Forest National Park
Species Related Feature Extraction

Classification of tree species on the basis of different features derived from remote sensing data and available site specific information

Which spectral/spatial features and data combinations generate the best results within a classification modelling approach?
Preprocessing Steps of Hyperspectral Data

1. Raw Data (DN)
   - Laboratory Calibration
   - Vicarious Calibration

2. At-sensor Radiance
   - Attitude and Position Data, DEM
   - Radiative Transfer Model, Meteorologic Data
   - Boresight Misalignment Angles

3. Orthorectified / Co-registered
   - Iterative Adaptive Smoothing Filter, Savitzky-Golay Filter

4. Ground Reflectance
   - Atmospheric Correction

5. Spectral and Spatial Polishing
   - Noise Removed

6. BRDF Correction
   - Illumination Effects Removed

7. Mosaicing
   - Binning

8. Seamless Mosaic
BRDF effects correction method (BREFCOR – ATCOR4) for an unsupervised, model based BRDF correction (surface-cover-dependent) of airborne wide FOV scanner data
Hyperspectral Data
VNIR / SWIR
(416 Bands,
3.2 m resolution)

Atmospheric correction using ATCOR 4

BRDF removal using BREFCOR

Create two Mosaics using ENVI 5.3

Identify ground truth data (Pixels)

Anonymous Pixels

Feature selection

Feature Engineering

Split into Training / Test data

Filter for outliers

Labled Pixels

Hyperparameter tuning

Chose best performing classifier

Train classifiers (for different Predictors)

Create Feature database:
(Spectral data, vegetation indices, LIDAR data)
Workflow
Forest / Tree Mask

✓ Ensures, that only trees are classified
✓ Prevents misclassification between trees and other vegetation

1. Discriminate between vegetation (NDVI ≥ 0.4) and non-vegetation (NDVI < 0.4)
2. Eliminate Forest gaps and low canopy heights
   (LiDAR derived tree heights < 1.5m)
In-situ Data

Set-up of training and validation data → reference data set

Depending on geometric resolution of remote sensing data:
Single trees → crown
Plots of trees → cluster of crowns / stands

Minimum number of samples
> 10 \cdot n \text{ pixels} \text{ (desirably } 100 \cdot n \text{ pixels})
where \( n \) = number of variables used to extract classes

Imbalanced training data set → down-sampling approach

Reference data set should cover all possible feature specific variations of the occurring tree species
Vegetation Indices

Photochemical Reflectance Index $PRI = \frac{\lambda_{531\text{nm}} - \lambda_{570\text{nm}}}{\lambda_{531\text{nm}} + \lambda_{570\text{nm}}}$

$\rightarrow$ e.g. vegetation productivity

Red Edge NDVI $RENDVI = \frac{\lambda_{750\text{nm}} - \lambda_{705\text{nm}}}{\lambda_{750\text{nm}} + \lambda_{705\text{nm}}}$

$\rightarrow$ e.g. general vegetation health

Red Edge Inflection Point $REIP = 700 + 40 \cdot \frac{\left(\frac{\lambda_{670\text{nm}} + \lambda_{780\text{nm}} - \lambda_{700\text{nm}}}{2}\right)}{(\lambda_{740\text{nm}} - \lambda_{700\text{nm}})}$

$\rightarrow$ e.g. chlorophyll content

Simple Ratio $SR = \frac{NIR}{RED}$

$\rightarrow$ e.g. estimation of over-story LAI

Normalized Difference Infrared Index $NDII = \frac{\lambda_{819\text{nm}} - \lambda_{1649\text{nm}}}{\lambda_{819\text{nm}} + \lambda_{1649\text{nm}}}$

$\rightarrow$ e.g. plant water content

Normalized Difference Lignin Index $NDLI = \frac{(\log_{\lambda_{1754\text{nm}}^{\lambda_{1754\text{nm}}}}) - (\log_{\lambda_{1680\text{nm}}^{\lambda_{1680\text{nm}}}})}{(\log_{\lambda_{1754\text{nm}}^{\lambda_{1754\text{nm}}}}) + (\log_{\lambda_{1680\text{nm}}^{\lambda_{1680\text{nm}}}})}$

$\rightarrow$ Lignin content
Structural and Topographic Features

- Tree height (DSM – DEM)
- Terrain height (DEM)
- Slope
- Aspect
- Shaded Relief
Validation Approach

- Evaluation of classification accuracy
- Test data set
  (statistical evaluation – confusion matrix)
- Visual interpretation
- Forest inventory
- Field survey
Accuracy assessment

Evaluation based on Cohen’s kappa and F-Scores

**Kappa:** $\kappa = \frac{(p_o - p_e)}{(1 - p_e)}$

$p$ is the observed agreement ratio, and $p$ is the expected agreement.

**F1 score:** $F1 = 2 \times \frac{\text{precision} \times \text{recall}}{\text{precision} + \text{recall}}$

$\text{precision} = \frac{tp}{tp + fp}$

$\text{recall} = \frac{tp}{tp + fn}$
Training Data

Forest Inventory 2002/2003
Training Data

Species composition northern part

- *Fagus sylvatica*: 17.9%
- *Picea abies*: 24.6%
- Hardwood & other Broadleaf: 0.3%
- Mixed mountainous forest: 9.1%
- Picea abies & other Broadleaf: 2.4%
- Picea abies & other Conifers: 1.5%
- Picea abies & Fagus sylvatica: 44.1%
## Training Data

<table>
<thead>
<tr>
<th>Species</th>
<th>English</th>
<th>Abbreviation</th>
<th>Pixels</th>
<th>Color</th>
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<tr>
<td><em>Abies alba</em></td>
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**Total pixel:** 4775

1/4 of this training data is held back for evaluation (Test set)
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Training Data

### Spectral data

<table>
<thead>
<tr>
<th>VNIR</th>
<th>SWIR</th>
<th>Vegetation Indices</th>
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<tbody>
<tr>
<td>131 Bands</td>
<td>133 Bands</td>
<td>9 Indices</td>
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### LIDAR data

<table>
<thead>
<tr>
<th>DTM</th>
<th>Treecount</th>
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<tbody>
<tr>
<td>Elevation</td>
<td>Stem density</td>
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![Spectral data graph](image)

![LIDAR data map](image)
# Training Data

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<th>LiDAR</th>
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## Results

### F1-Scores

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Results

SWIR + Spectral indices + DTM + Treecount

[Map and graph showing predicted percentages of different tree species]

- Abies alba
- Betula pendula
- Larix decidua
- Populus tremula
- Acer pseudoplatanus
- Fagus sylvatica
- Picea abies
- Pseudotsuga menziesii
- Alnus glutinosa
- Fraxinus excelsior
- Pinus mugo
Results

VNIR + SWIR + Spectral indices

[Map showing vegetation distribution with labels for different tree species]

Predicted percentages:

- Abies alba: 14.34%
- Acer pseudoplatanus: 0.30%
- Betula pendula: 0.50%
- Fagus sylvatica: 34.09%
- Larix decidua: 38.41%
- Picea abies: 38.17%
- Populus tremula: 1.27%
- Pseudotsuga menziesii: 0.22%
- Pinus mugo: 0.01%
Results

Validation based on spatial distribution and overall percentages
Results
Confusion Matrix

### VNIR

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Results
Confusion Matrix

VNIR+SWIR+Indices

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VNIR+SWIR+Indices+Treecount+DTM

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Predicted label
Results
Confusion Matrix

VNIR+SWIR

VNIR+SWIR+Indices
Results

Number of trees vs. OOB error rate for VNIR and SWIR.
Results

Spectral normalized Confusion Matrix
Results

Probability of predictions
Results

Probability of predictions
Conclusion I

- Full spectral coverage (VNIR-SWIR) was very useful
- Spatial resolution of 3.2 m was sufficient
- Training data sampling is difficult, especially for the minority classes
- Structural information e.g. tree count was beneficial
Conclusion II

Development of multi-source approach for tree species classification in the Bavarian Forest National Park

Final analysis with Random Forest revealed successful discrimination of tree species with an overall accuracy of 94%

Application of spectral, structural, and topographic information increases the separability of species having similar spectral signatures

BUT: high classification model accuracy does not necessarily reveal the real map accuracy
Conclusion III

- Caution must be taken when integrating the elevation parameter
  - training and test data set should cover all possible terrain specific variations of the occurring tree species

- Over-representation of European larch due to the strong similarity to Norway spruce; Lowest classification accuracies for European white birch, Scots pine and European rowan
  - misclassifications due to the low number of available reference data
Outlook

- Transfer Classification algorithm to Šumava NP
- Include phenological information (multitemporal SPOT 5)
- Discriminate between dense and open stands
- Multitemporal analysis
Tree species naming conventions

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Contact details

Dr.
Nicole Pinnel
DLR
E-mail: nicole.pinnel@dlr.de
Tel.: +49 8153-28-1130