tags: `2nd joined field course EarthObservationNetwork`, `12.-16.09.2022`, `Waldhaus Oderbrück`, Forest Inventory and Remote Sensing, University Göttingen,

Dr. Hans Fuchs, hfuchs@gwdg.de

Bark_Beetle_UAS: Detection of bark beetle infestation in spruce plantations using multispectral drone images

Background

Since 2019 a bark beetle (*Ips typographus*) outbreak in Harz mountains induce large economic and ecological problems in spruce forests. Large area changes call for adapting forest management and monitoring systems.

In a pilot project of the Chair of Forest Inventory and Remote sensing, University Göttingen, drone flights were conducted in the forest district Clausthal, state forest lower saxony. Image data were acquired on 10.05.2022 using a RGB and a multispectral Sensor (s.Tab. 1). Digital ortho photo mosaics were produced and provided in a WebGIS (Fuchs, Nölke und Magdon (2022), http://wwwuser.gwdg.de/~hfuchs/altenau/).

Table 1. Spectral resolution of the multispectral sensor RedEdge-MX.

Bandno.	Spektral range	Wave lenght [nm]
1	Blue	475
2	Green	566
3	Red	668
4	RedEdge	717
5	Near IR	842

Following resarch question should be answered:

1. Are multipsectral drone images are suited to detect bark beetle attack?
2. Can an automated object-based image analysis(OBIA) distinguish different stages of the tree dieback?

Objectives

- Know main steps of an OBIA process workflow.
- Selectiing training data for a supervised classification.
- Extracting features for classifying image segments.
- Application of deep and a shallow neural networks.
- Creating validation points based on stratified random sampling with equal allocation.
- Apply stratified estimators for accuracy and bias adjusted area proportions.

Prerequisites

- Windows10 64bit: R and RStudio Installation http://wiki.awf.forst.uni-goettingen.de/wiki/index.php/R_installation

Exercise

Download the folder *Bark_Beetle_UAS* in the gitup repository EON2022 to a local folder. Open the Rscripts in subfolder */src* with RStudio. Send code to the R-Terminal line by line.

01 Data Preparation

Tutorial data are downloaded from cloud storage. raster data are read as single and multi bands and visualized.

Histograms and image statistics inform on data type and range.

Remove the transparency channel No = 6 for subsequent analyses.

Resampling aggregates pixel size from 9cm to 18cm an reduces data size with factor 4.

02. Image Enhancement

Beside the original 5 bands Marx (2010) proposes spectral indices sensitive to changes of chlorophyll content:

- RedEdge NDVI
- Green NDVI
- RATIO
- Chlorophyl Green Model
- Clorophyll RedEdge Model.

The result is saved together with the original bands as an image stack of 10 bands.

03 Feature extraction

In OBIA we look not only at instances on pixel level but also on spatial neighborhoods which are built by image regions or segments. Spatial context is favourable especially for high spatial resolution sensor data.

The OBIA work flow starts with a segmentation which divides the image into regions. Here we use the result of a deep learning instance based segementation using a 2D multispectral ortho photo as input. The model is parametrized by a large amount of training data (Freudenberg et al. 2022).

For each segment we calculate simple descriptive statistical measures (mean, standard deviation) using all pixel values inside a segment.

Excursus: Selecting training data

Training data are non-statistically selected on basis of image segements with describing features. Polygons are selected and labeled on screen. As reference source a false color composite of the ortho photo mosaic is interpreted. Following classes are defined: (s. Marx, 2010):

C_ID	Attribute	Properties	Color code
1	Healthy	Spruce needles green an vital	#4d4dff
2	Infested	Spruce needles green and reduced vitality	#fbd931
3	Red	Spruce needles red brown, with or without defoliation, dying or dead	#ed0808
4	Broadleaf		#80ff00

Training data may be selected in QGIS:

- Load the drone ortho photo *UAS_image.tif* and display a false color composite RGB = 4,2,1
- Load the segmentation result with extracted attributes as vector file `tpolygons.gpkg` into the map canvas.
- Change symbology of polygons from "filled" to "no brush", stroke color = white.
- Add an additional column "*C_ID*" to the polygon attribute table.
- Select polygons of a vitality class and insert the class code in column *"C_ID"*. For each class choose the same sample size (minimum 25).
- Select all labeled polygons and save them in a new vector file.
  - Export > Save selected features as ...
- Drag and drop the legend *legend.csv* into the Layers window. Join attribute tables of the layer *train_polygons.gpkg* and *legend.csv* on the common field *"C_ID"*.

These work steps may be skipped by using an already prepared file:

`train_polygons.gpkg`

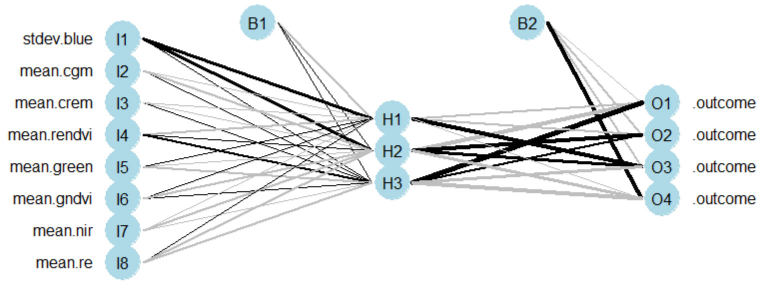
04 Feature selection, training and classifikation

Here we apply classical methods of machine learning.

In the process of feature extraction we reduce the number of features and using recursive backward selection of the ensemble classifier randomforest.

Reduction and selection of best suited variables or variable groups lead to more robust models that may be better generalized on new data.

An additional classifier is a shallow neural network with 8 input neurons, one hidden layer with 3 neurons und 4 output classes.



Finally the classication model is applied on all image segments.

05 Validation Sampling

The resulting thematic map is imperfect and provides only a generalized model. The map information is (only) useful for a user if the map quality is known. A statistically rigorous evaluation of the map quality should be viewed as an essential part of any remote sensing project.

We create a point validation file using stratified random sampling with equal allocation.

We collect validation data by visual interpretation of a false color composite of the ortho photo mosaic. Vitality classes are assigned at the validation point location. Enter the class code in column *C_ID* added to the attribute table of the point validation file.

06 Stratified Validation

We build error matrices and calculate accuracies using naive and stratified estimators. Then, we adjust the bias of area proportions.

Task

1. Analyze the vitality of spruce trees after bark beetle attacks using a shallow neural network.
2. Display the result as a thematic map using the proposed color table (Tab. 1) with the ortho photo mosaic as background.
3. Save the Map display as PNG:

- Project > Import/Export > Export Map as Image …

4. Compare the accuracies of randomforest and shallow neural network.

References

Freudenberg, M., Magdon, P. and N.Nölke (2022): Individual tree crown delineation in high-resolution remote sensing images based on U-Net. Neural Computing and Applications. https://doi.org/10.1007/s00521-022-07640-4

Fuchs, H., Nölke, N. und P. Magdon, (2022): Drohnenbefliegung des Forstrevieres Altenau im Forstamt Clausthal-Zellerfeld am 10.5.2022. Url: http://wwwuser.gwdg.de/~hfuchs/altenau/

Marx, A. (2010): Erkennung von Borkenkäferbefall in Fichtenreinbeständen mit multi-temporalen RapidEye-Satellitenbildern und Datamining-Techniken. PFG 2010/4,S. 243 – 252.

Olofsson, P., Foody, G. M., Herold, M., Stehman, S.V., Woodcock, C. E. and Wulder, M. A. (2014): Good practices for estimating area and assessing accuracy of land change. Remote Sensing of Environment,Volume 148, 2014, ISSN 0034-4257, http://dx.doi.org/10.1016/j.rse.2014.02.015

Ortmann, A. 2017: Stratified sampling tool for area estimation. https://github.com/openforis/accuracy-assessment

Stehman, S.V., Foody G.M. (2019): Key issues in rigorous accuracy assessment of land cover products, Remote Sensing of Environment,Volume 231,2019,111199,ISSN 0034-4257, https://doi.org/10.1016/j.rse.2019.05.018