Biodiversity Monitoring based on Remote Sensing - Assessment of Forest Height Changes Considering Inaccuracies in Image-based Digital Elevation Models

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Abstract: Multitemporal monitoring of vegetation heights holds great potential for forest management and protection. For this purpose, time series of image-based digital elevation models can be used. However, the determination of forest height changes is challenging due to missing reference data and varying quality of the input data. In this study, a method is developed for automatic classification of forest height changes considering inaccuracies in elevation information. To analyse these inaccuracies, heights of buildings scattered throughout the study area were analysed. Based on this analysis, height changes were classified into i) stable ii) stable/growth iii) growth and iv) decline. The developed methods create a change map for each user-defined forest area within Baden-Württemberg, showing forest height changes over six years and provide the potential for a long-term, remote-sensing based biodiversity monitoring.

1 Introduction

Forest structures are essential elements of forests, which are linked with habitat requirements of many protected species (FRANK et al. 2009; KYWE 2012). Old forest stands in particular are rich in structure and essential for carbon storage and –sequestration, as well as for water provisioning and buffering of the microclimate (SPRACKLEN & SPRACKLEN 2019; DE ASSIS BARROS & ELKIN 2021). Old trees play a vital role as habitats for plant, fungus, lichen and animal species that depend on these conserved structures and cannot compete in younger stands, which are often characterized by denser and uniform planting and have unstructured, linear forest edges (BOLLMANN et al. 2009). Unfortunately, despite the high awareness in the European Union about these forests, their abundance is still declining (KNORN et al. 2013; SABATINI et al. 2018). In addition, forest age and vegetation height are important information for management and for the designation of protected areas (VIHERVAARA et al. 2017). Therefore, it is important to monitor forest development in a goal-oriented manner, as discussed in LINDENMAYER & LIKENS (2009) and REYNOLDS et al. (2016).
However, identification of old stands and measurement of tree growth in the field is difficult, destructive and time-consuming (SPRACKLEN & SPRACKLEN 2019). Remote sensing techniques such as airborne laser scanning (ALS), aerial images or satellite data are a cost efficient and promising approach for biodiversity monitoring (JIANYA et al. 2008; KUENZER et al. 2014; VIHERVAARA et al. 2017). Time series of vegetation height changes can help to identify undisturbed, well-growing forest stands for entire landscapes (SPRACKLEN & SPRACKLEN 2019) or countries (GINZLER et al. 2021) and may enable the distinction of old and younger forest stands.

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So far, there are no established remote sensing-based monitoring tools for Germany that analyse forest height changes over time.
As a contribution to the project "monitoring of biodiversity with remote sensing tools" (MoBiTools), this study developed remote sensing-based methods to record biodiversity-relevant forest surface structures. For this purpose, image-based digital elevation models were used which cover about one third of the state area of Baden-Württemberg every year and thus provide new data every three years (LANDESAMT FÜR GEOINFORMATION UND LANDENTWICKLUNG (LGL) 2021b). A key analysis was the change of vegetation heights, which can be derived from normalized digital surface models (nDSMs). However, the spatially explicit assessment of height changes is challenging: Reference data are rarely available. If reference data is available, the accurate location of reference points and tree canopies, as well as the measurement of tree heights, are subject to uncertainties (ACKERMANN et al. 2020). Moreover, the aerial images from different flight campaigns can differ in quality (ZIELEWSKA-BÜTTNER et al. 2016), and nDSMs can also suffer from inaccuracies for various reasons (WANG et al. 2015; ACKERMANN et al. 2020; JAVADI et al. 2020), which may affect classification. Therefore, a marked change in forest height can only be measured if height change is greater than any biases in the remote sensing measurement (WULDER et al. 2008). This implies that growth increment must exceed the assumed measurement bias (WULDER et al. 2008). Hence, to detect changes, the vertical agreement of the nDSM time series must be evaluated and considered when classifying forest height changes. Consequently, the following research question arises: How can height changes in forests be assessed taking into account inaccuracies in image-based digital elevation models?

2 Methodology

After a short introduction to the study site (2.1), this section describes the nDSM time series as input data for the assessment of forest height changes (2.2), the accuracy assessment of these datasets (2.3) and the change detection of forest heights considering inaccuracies in the input data (2.4). The developed workflow was accomplished using the software R Version 4.0.5 (R CORE TEAM 2021).

2.1 Study site

The study site covers the forest area of Baden-Württemberg, a federal state located in the south-west of Germany. Baden-Württemberg has a total area of about 35,751 km², of which around 40 % (13,718.5 km²) are covered with forest (KÄNDLER & CULLMANN 2014). Most common tree species are Norway spruce (*Picea abies*) with 34 %, European beech (*Fagus sylvatica*) with 22 %, Silver fir (*Abies alba*) with 8 % and oaks (*Quercus sp.*) with 7 %.

2.2 Creation of nDSM time series

The assessment of forest height changes was carried out using aerial images acquired by 82 airborne image flight missions spanning the period from 2011 to 2019. The aerial images were provided by the state agency of spatial information and rural development of Baden-Württemberg (LGL) (LANDESAMT FÜR GEOINFORMATION UND LANDENTWICKLUNG (LGL) 2021b) as part of

regular aerial surveys. The surveys are conducted during the vegetation period on a three-year cycle, covering about one-third of the state each year. Using the software SURE of nFrames (ROTHERMEL et al. 2012), photogrammetric point clouds were processed with a ground sampling distance (GSD) of 40 or 50 cm. Flight conditions such as season, time of day and weather conditions, flight settings such as front/side overlap and camera type, as well as image-matching parameters such as SURE version and GSD, varied between the flight missions.
Normalized digital surface models (nDSMs) with a GSD of 1 m generated from aerial images served as the basis for deriving forest heights. A detailed description of the applied methods for deriving aerial image-based nDSMs can be found in SCHUMACHER et al. (2019) and GANZ et al. (2020). The three-year interval of the image flight missions resulted in the time series 2011-2014-2017, 2012-2015-2018, and 2013-2016-2019. The position of the flight missions per year and the composition of the time series are shown in Figure 1. The allocation of relevant flight missions is defined by a regularly updated polygon feature that indicates, in 1x1km squares, the combination of flight missions to be selected for each single year and three-year interval.

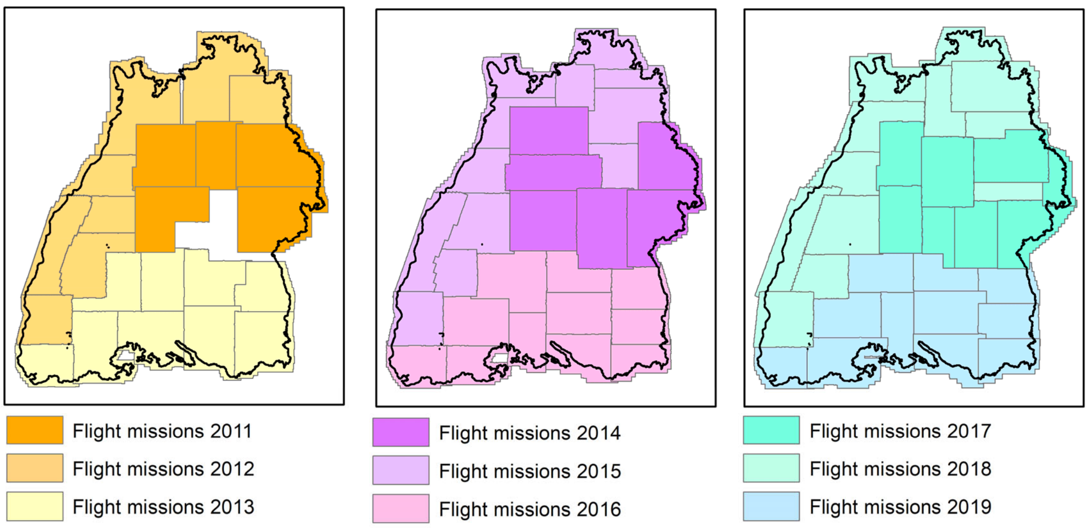

Fig. 1: Flight missions in Baden-Württemberg between 2011 and 2019 are combined into the three time series 2011-2014-2017, 2012-2015-2018 and 2013-2016-2019

2.3 Accuracy assessment of nDSM time series

Within the last decades, various remote-sensing-based methods for the assessment of tree height at stand or single tree level have been developed and studied. The comparison of remote sensing methods for measuring tree height involves a high degree of uncertainty because data acquisition parameters and forest characteristics vary in these studies. As such, it is difficult to transfer measurement errors between the applied methods (GANZ et al. 2019). As a consequence, the evaluation of the accuracy of forest heights cannot be measured against the results of other studies. Depending on the remote sensing system, forest heights can be systematically under- or overestimated. Therefore, in time series analyses, besides the absolute accuracy of the nDSMs, especially the precision of repeated recordings is crucial (WULDER et al. 2008). To evaluate the vertical agreement of the nDSMs, the variation of objects at constant heights was quantified. For this purpose, the building dataset of the land register of Baden-Württemberg (LANDESAMT FÜR GEOINFORMATION UND LANDENTWICKLUNG (LGL) 2021a) was used. A maximum of five buildings per 1x1km quadrant was randomly sampled across Baden-Württemberg so that the buildings were distributed as evenly as possible. For each building, the maximum value of the respective nDSM was extracted for each year of the time series. As the accuracy assessment aimed to determine the nDSM precision rather than changes in buildings, according to the study of DINI et al. (2012) a threshold was set. Only buildings with heights > 2.5 m were evaluated. Furthermore, only nDSM height differences < 2.5 m were considered. Height changes > 2.5 m were considered as architectural changes and were not analysed. Only buildings for which data were available for all three time periods were used.

After applying the thresholds, 87225 building heights could be extracted from three different nDSMs, respectively. The nDSM inaccuracies were evaluated on the basis of the maximum absolute differences of each time series. The distribution of the buildings considered for accuracy assessment, as well as a histogram of the maximum absolute differences, is shown in Figure 2. The maximum absolute differences were ranging between 0 and 2.50 m with a mean value of 0.88 m (standard deviation = 0.46 m). A value of 2 m corresponded to the 97% percentile.

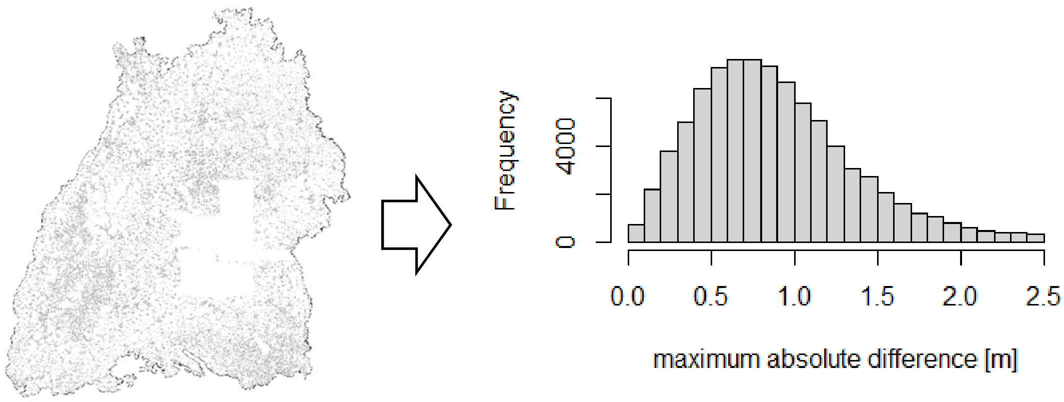

Fig. 2: To evaluate the accuracy of height changes, nDSM values were extracted at 87225 buildings. The maximum absolute differences between nDSMs were calculated to evaluate the vertical agreement of the nDSM time series

2.4 Classification and plausibility check of forest height changes

To minimize inaccuracies at the level of individual pixels, the resolutions of the nDSMs were reduced from 1 m to 10 m, keeping the highest values. Subsequently, the height changes were calculated by subtracting the rasters from each other resulting in nDSM difference rasters (D-nDSMs). Based on the nDSM time series 2011-2014-2017, 2012-2015-2018 and 2013-2016-2019, changes could be analyzed over 6 years as well as over two three-year periods.

Height changes were classified as follows: i) stable, ii) stable/growth, iii) growth, iv) decline. The division of the classes 'stable', 'stable/growth' and 'growth' is based in the height change within six years: The class 'stable' covers height differences of < 1 m to restrict height changes to a minimum, while the class 'growth' comprises height differences of > 3 m. Based on the estimated inaccuracy of the nDSM time series, a range of 2 m (1 – 3 m height difference) was assigned to the class 'stable/growth' to distinguish between the classes 'stable' and 'growth'. The allocation

to the class ‘decline’ was made on the basis of the three-year periods. A significant height reduction of more than 50% of the maximum measured tree height had to occur in one of the three-year periods.
In order to verify the plausibility of the height changes, all available time periods were considered, including two three-year periods and one six-year period. Pixels with non-plausible height changes were not assigned to any category. For example, an increase in height (> 1 m) followed by a decrease in height of the same magnitude was considered to be implausible, since it was presumably due to inaccuracies in the nDSMs. The permitted height changes within the three- and six-year periods are illustrated in Figure 3 and summarized in Tab. 1.

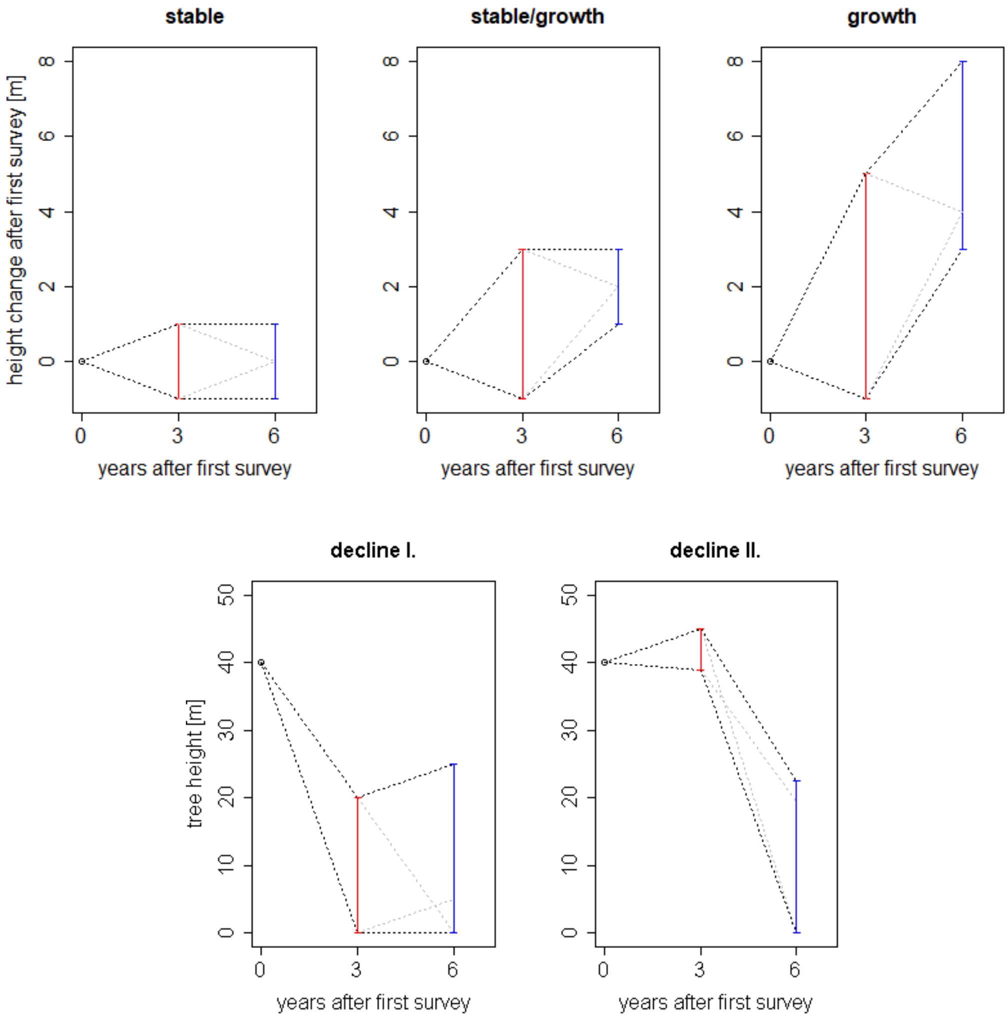

Fig. 3: Categorization of nDSM height changes as ‘stable’, ‘stable/growth’, ‘growth’ and ‘decline’. Height changes are only allowed in the ranges shown: Both after 3 years (red line) and after 6 years (blue line) a plausibility check was conducted. The grey lines correspond to the allowed ranges within the class definition assuming the height development reaches a maximum or minimum value after three years.

Tab. 1: Classification and plausibility check with d as difference between the nDSMs of the time period. The time period defines the analysed height difference after the first survey. Bold values are for classification, the others for plausibility check

Time period	stable	stable/growth	growth	decline
0 to 6 years	**-1 m < d < 1 m**	**1 m < d < 3 m**	**3m < d< 8 m**	**-**
0 to 3 years	-1 m < d < 1 m	- 1 m < d < 3 m	- 1 m < d < 5 m	**i) d < 50% of tree height** OR ii) d < 5 m
3 to 6 years	-1 m < d < 1 m	- 1 m < d < 3 m	- 1 m < d < 5 m	i): d < 5 m OR **ii): d < 50% of tree height**

3 Results

By combining the aforementioned approaches, a tool could be created that automatically evaluates forest height changes for any given area in Baden-Württemberg. While a polygon dataset with the requested areas serves as input dataset, the outputs of the tool are a table with summarized results (*.txt), which are illustrated by graphs and maps for each area (*.png), and optionally raster datasets (*.tif). Thus, spatial and temporal analyses are possible, which can be integrated in research questions regarding biodiversity. Figure 4 shows the developed workflow and illustrative results for four stands of Norway spruce at different ages. The stands are located in the southern Black Forest on comparable site conditions. The examples show that, despite the short time period covered by the time series so far, the proportions of the classes can be very different across stands at different ages. Stand 1 with an age of 31 – 40 years shows with 79% a very high percentage of the change class 'growth'. The stand 2 and 3 with the ages 61 – 70 years and 81 – 90 years have a mixed proportion of the classes 'growth' and 'stable/growth', with 41% and 24% 'growth' and 27% and 47% 'stable/growth', respectively. 28% and 26% each are assigned to 'NoData'. In stand 2, height reduction was detected on 3% of the area. Stand 4 represents with an age of 121 – 130 years a late-successional forest and shows with 35% 'stable', 2% 'growth' and 30% 'NoData' a high percentage of constant heights and 'NoData'. In these examples, the class 'stable' increases with age while class 'growth' decreases. This is consistent with the general finding that height growth of young stands is greatest and decreases with age (PRETZSCH 2019). Although the examples are generally not representative for stands with different tree species, ages, and site conditions, they show that a differentiation of height changes may be possible i) according to the set of categorizations made and ii) across the available time series.

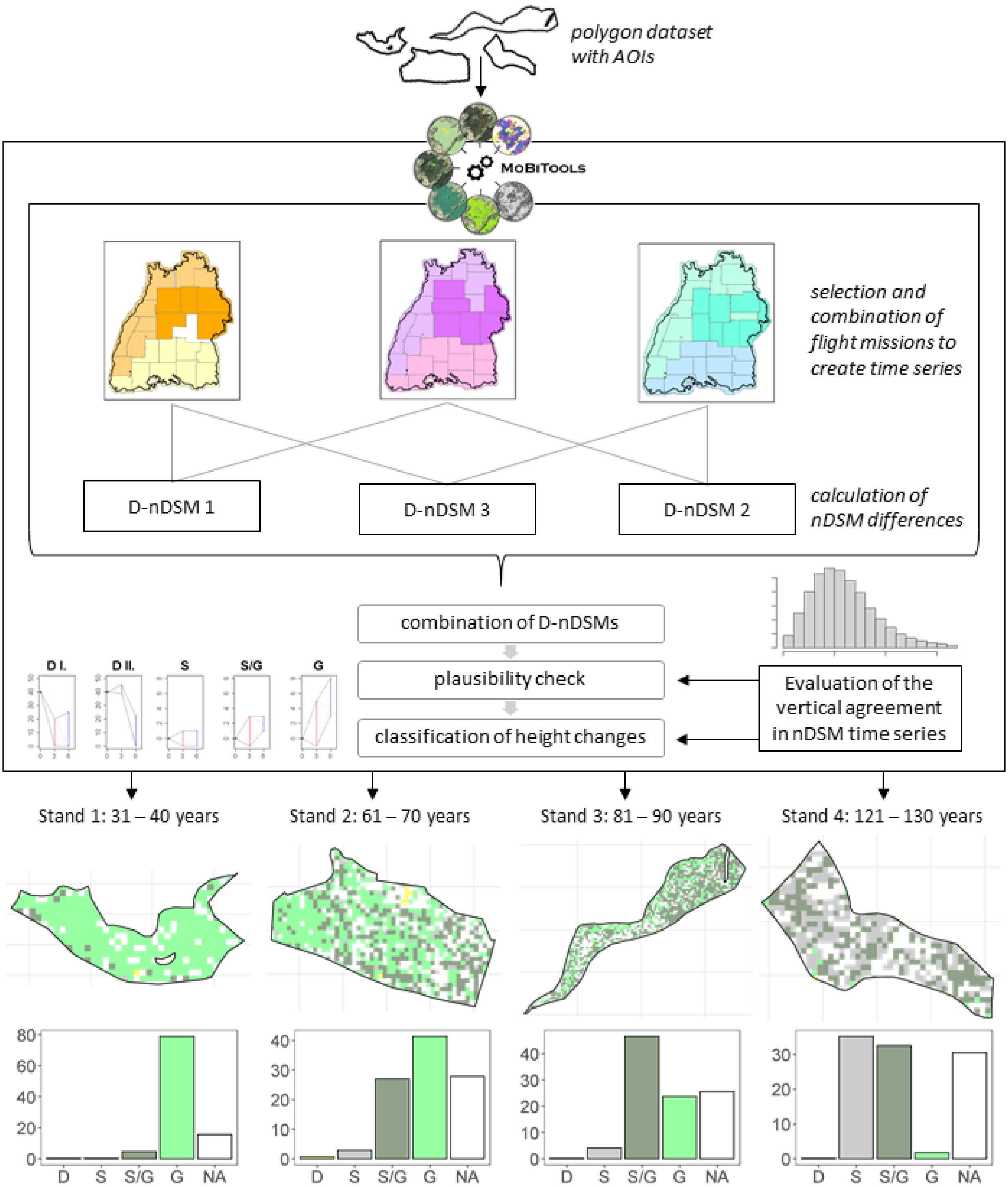

Fig. 4: Developed workflow leading to the assessment of forest height changes for user-defined forest stands in Baden-Württemberg. D-nDSMs are nDSM difference rasters. Graphs with D = decline, S = stable, S/G = stable/growth, G = growth, NA = NoData. The y-axis depicts the percentage of the area

4 Discussion

Continuous change detection based on multitemporal aerial images is a challenge due to variant spectral characteristics, shadows and surface conditions (JAVADI et al. 2020). Changes in the acquisition geometry, the time of acquisition, the weather at the time of flight (ACKERMANN et al. 2020) as well as different view and illumination directions (DINI et al. 2012) influence image-matching for deriving elevation models. Especially in rugged terrain and forests of complex structure, image-based elevation models might be erroneous (HOBI et al. 2015; ZIELEWSKA-BÜTTNER et al. 2016). A direct comparison of height models within a time series can therefore lead to uncertainties and artefacts (ACKERMANN et al. 2020). As a consequence, it is very important to note that changes in tree height can only be measured if the height increase is greater than any biases in remote sensing measurements (WULDER et al. 2008). For that reason, we evaluated the vertical agreement arising by subtracting image-based nDSMs through the analysis of height changes on roofs. Despite filtering by 2.5 m, we cannot exclude the possibility of architectural changes on the analysed roofs. However, due to the high number of samples, the evaluation can be considered reliable. According to the accuracy assessment of 2.3, overlaps between the classes 'stable' and 'growth' can occur in approximately 3% of the samples.
The accuracies of elevation models vary regarding different land cover categories and provide lower accuracies in forests (ALGANCI et al. 2018). Furthermore, artefacts in elevation models are more frequent in forest areas than in non-forest areas (WANG et al. 2015). Consequently, the threshold for forest areas must be higher than indicated by the analysis of the roofs. A study of GANZ et al. (2019) evaluated the accuracy of tree height measurements based on aerial images from LGL. The accuracy for 30 individual tree heights on a 50-year-old Douglas fir (*Pseudotsuga menziesii*) stand in the Black Forest in Baden-Württemberg was estimated to range between 1 – 2 m. Finally, the accuracy of the measurement depends on the shape of the tree or on treetop visibility (GANZ et al. 2019). According to these findings, the range of 2 m of the class 'stable/growth' can be considered sufficient for differentiation between the classes 'growth' and 'stable. According to these findings, a threshold value of 2 m for the determination of height changes can be considered to be sufficient. In order to reduce misclassifications, the forest height changes must lie between certain thresholds to be assigned to one of the change classes. The class 'stable/growth' with its range of 2 m acts as a buffer between the classes 'stable' and 'growth' and thus contains both: areas where tree growth takes place and areas with stable forest heights. To further minimize misclassifications, we decreased the resolution of the nDSMs from 1 m to 10 m keeping the highest value within 10x10 m. As recommended by ACKERMANN et al. (2020), we filter out erroneous data through plausibility check during categorization. However, the relevance and correct categorization of the classes 'decline', 'stable', 'stable/growth' and 'growth' cannot be verified due to the absence of reference data.
As the examples show, the results of the time series analysis have the potential to correlate with forest age. Therefore, the nDSM time series can potentially enable the distinction of old forests from younger forest stands. For which tree species, tree age and site conditions this is practicable needs to be further investigated. As height growth is greatest in young trees under good site conditions, the developed methods are only appropriate until a specific forest age and site index.

For older stands with a lower site index, it takes considerably longer for the height increment to exceed the bias of the D-nDSMs. We agree with WULDER et al. (2008) that there is likely to be some error and that this error has to be contrasted with expected growth. For example, tree growth can vary with age and site conditions for Douglas-fir from 0.35 to 1.12 m per year for a 10-year-old stand, from 0.10 - 0.36 m per year for an 80-year-old stand, and from only 0.05 - 0.24 m per year for a 120-year-old stand (WULDER et al. 2008). This illustrates that the present 'stable' and 'growth' classes might be applicable for analysing the age structure of forests, though presumably only under good site conditions. As the examples show, the amount of 'NoData' increases with increasing forest age or stand complexity. The 'NoData' pixels are either related to inaccuracies in the nDSM time series or to heights < 5 m. Old-growth and late-successional forests possess complex structures (FRANK et al. 2009), which complicates the analysis of time series. To be able to evaluate change detection in forests with complex structures or poor site conditions, longer time series are needed.
The required time interval of the images depends not only on the research question but also on the availability of data, e.g. the frequency of aerial image flight missions (ACKERMANN et al. 2020). For our studies, the aerial images were available from 2011 to 2019, resulting in time series of six years. Compared to other studies, the provided time series is very short. VASTARANTA et al. (2015) classified forest stand age using time series of image-based DSMs over a 68-year period. GINZLER et al. (2021) analysed forest height changes with historical vegetation height models based on analogue aerial photographs from the time periods 1980 and 1990 and the current vegetation height model from 2010. The greater the interval between the recording dates and the longer the time series, the more detailed the information on forest height change. With longer time series, the class 'growth' could be further distinguished to differentiate between slow and fast growing forests. High frequency of data recording enables very precise identification of forest dynamics. The three-years interval is sufficient to detect changes in a regular high frequency. At 10×10m, it is possible to detect even small changes in very small groups of trees. When time series grow longer, the current analysis tool, especially the plausibility and categorisation, must be adjusted.

5 Conclusion

Remote sensing enables the observation of natural dynamics that make it a powerful tool for biodiversity-related studies (KUENZER et al. 2014). The derivation of forest stand age (SCHUMACHER et al. 2020) or the identification of the amount and location of old forests (DE ASSIS BARROS & ELKIN 2021) can aid both forest management and forest conservation strategies. Regularly updated image-based digital elevation models from public flight mapping campaigns bear the potential to assess forest height changes in a cost-efficient way, especially when aiming at long-term monitoring. With the methods developed, it is possible to monitor forest height changes over the last six years for a given forest area in Baden-Württemberg. The results can potentially give an estimate of forest age or the proportion of old forests. The calculations are fully automated for a user-defined number of areas and thus offer the possibility to get an overview of entire protected areas as well as individual habitats. Using an appropriately designed workflow, repeated aerial images enable measurement of forest height growth and the differentiation between tree loss, growth and stable heights over time, giving insights about changes in forest structures and habitats. Although the time series of only six years are still very short for forestry purposes, they already have the potential to contribute to an increase in information. Furthermore, the analyses show the potential of longer time series analyses. If new data sets are added to the time series analyses in the future, the developed analyses can be improved and extended. Therefore, this analysis can be considered as the beginning of a long-term, remote sensing-based biodiversity monitoring program to assess changes of ecologically important forest structures and habitats.

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