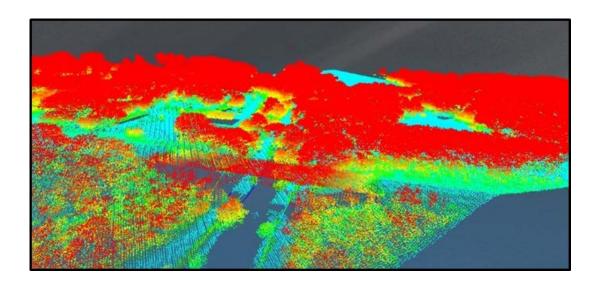


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of the German Centre
for Rail Traffic Research

Report 10 (2021)

Individual Tree Detection and Characterization along Railway Tracks

Summary



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Individual Tree Detection and Characterization along Railway Tracks Summary

by

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Table of contents

1	Introduction	7
2	State of research and methodological overview	8
3	Methods	9
3.1	GIS-Tool	9
3.2	Data acquisition	9
3.3	Data preparation	10
3.4	Tree detection	10
3.5	Tree characterization	11
4	Results	14
4.1	Visualization	14
4.2	Validation of the results	15
4.2.1	Filtering power lines	15
4.2.2	Tree species classification	16
4.2.3	Tree recognition	16
5	Discussion	18
6	Summary	19
7	Figures	20
8	Tables	21
9	References	22

1 Introduction

Extreme weather conditions in connection with trees near the railroad track represent a great danger for the rail infrastructure. Due to their high wind resistance, trains are usually not directly affected by storms, but objects falling on the railroad tracks represent a great danger. Fallen trees can affect the overhead lines as well as blocking the tracks, leading to train cancellations and delays or directly damaging trains and people. Deutsche Bahn (DB) Netz AG invested over € 100 million in the implementation of the vegetation management "Action Plan Vegetation" (BM 2018). In 2017/2018 alone, severe storms caused train cancellations or delays and track damage amounting to millions within a few months (WEIHGOLD 2018). A large proportion of the expenditure in the context of vegetation management is required for the manual inspection of the vegetation along the tracks. Because there is still no digital mapping of vegetation along the German railway lines. Instead, regular on-site visits and inspections of the vegetation must be carried out. However, these are time-consuming, costly and the height of the vegetation is only estimated (DB NETZE 2019: 36).

In general, a tree creates a risk of wind throw if its height exceeds the distance to the infrastructure or the infrastructure element. Other factors are the local topography, geology, soil properties, moisture of the subsoil, as well as the tree species and the health of the tree. Remote sensing methods represent a sensible alternative and, above all, a supplement, as they enable fast and objective individual tree detection and direct measurement of vegetation heights. This can result in less effort and associated cost reductions. With the help of automated analyzes of digital remote sensing data, this research project aims to support up-to-date and area-wide monitoring of the trees on railway lines.

- Detection and delimitation of individual trees
- Designation of potentially endangered tree populations

Since the data in these two federal states are freely available, the calculations are carried out using the federal states of North Rhine Westfalia and Thuringia as examples. The calculations are carried out in a process chain specially developed for this application, which is implemented as a GIS tool and also enables transfer to other areas.

To develop the research questions and goals, the project is divided into different automated sections, which in turn can be found in the structure of the GIS tool. Based on the current state of research and a methodological overview, the basis of the project is the data sighting and review. This is followed by data acquisition for the federal states of Thuringia and North Rhine-Westphalia in order to guarantee an exemplary calculation. The collected data is then used to enable comprehensive tree recognition and characterization. The results of these analyzes are then comprehensively validated and evaluated.

2 State of research and methodological overview

Individual tree detection (ITD) along large study areas is not a completely new research field in remote sensing. ITD based on remote sensing data has been the subject of research since the 1980s (ZHEN et al. 2016: 2). The most common, large-scale application is in the field of forestry for the creation of tree registers and the collection of tree properties such as the position, the height or the tree species (HYYPPÄ et al. 2009: 338). However, the possible uses must not only be reduced to closed forests. Other areas of application are, for example, urban areas for spatial planning purposes (HÖFLE & HOLLAUS 2010: 281) or the measurement of green volume (YAO & FAN 2013: 1). What unites the different fields of single tree recognition is the need for high resolution, freely accessible data and the basic methods of generation of desired information from these data sets.

In the course of the European INSPIRE directive, a uniform spatial data infrastructure is aimed at with which an international and national exchange of spatial data is pursued. In this context, the Open Data Act should be mentioned as part of the E-Government Act, which came into force on July 13, 2017 (BUNDESANZEIGER VERLAG 2017). Since then, the availability of open spatial data from the federal offices has been increasing, which means great potential for science and companies. In addition to Berlin, Thuringia and North Rhine-Westphalia already offer large parts of their data in an open spatial data infrastructure. The challenge therefore turns from the availability of geospatial data into the management of large amounts of data.

Process development with Python is used to process raster, vector and point data in this research project. Due to its functionality and distribution, this programming language is one of the most popular for editing geodata (LAWHEAD 2019). Graphic surfaces can be designed with the help of the "Tkinter" library. With the "pyinstaller" library, these can also function as independent programs.

One of the main functions of the GIS tool developed as part of the project is the detection of individual trees. Most of the common methods are based on the same principles. It is assumed that the top of the tree is at the maximum value of the normalized digital surface model (nDSM) and that this value becomes smaller towards the crown boundary. According to KE & QUACKENBUSH (2011), the most widely used representative of algorithms for single tree recognition is the local maximum (LM) method, whereas the watershed segmentation (WS) is often used as an algorithm for tree canopy delimitation. With these methods, accuracies of 80–90% can be achieved in a homogeneous forest stand (ZHEN et al., 2016). The accuracies can vary depending on the variation of the tree species, stand density, age, size or crown overlap (LARSEN et al., 2011). Another difficulty in recognizing trees using elevation data is the distinction between trees and non-vegetation. One solution is often the use of spectral data (CHU et al. 2019).

The tree characterization of identified individual trees focuses on growth modeling and risk assessment. In growth modeling, the Chapman-Richards growth function (Formula 1, RICHARDS 1959) is one of the most common three-parametric functions (PRETZSCH, 2019). Function parameters can be derived with the help of tree heights and age in the case of extensive inventory levels. For risk assessments, multi-criteria analyze (MCA) are a suitable means of weighing up several factors against each other. These are often used as decision-making aids in various areas, for

$$H(t) = a (1 - e^{-bt})^c$$

H(t): Tree heigth
a, b, c: Function parameters
t: Tree age

example in economics. In particular, when used in a GIS, spatial distinctions or location decisions can be made here (MALCZEWSKI, 1999; EASTMAN 1999, MALCZEWSKI, 2006). By using Fuzzy Membership functions, factors can be standardized. The Ordered Weighted Averaging (OWA) approach is used to adjust the measure of trade-off and risk between the factors (JIANG & EASTMAN 2000).

3 Methods

3.1 GIS-Tool

The high spatial resolution of 1 m (digital surface model [DSM] / digital terrain model [DTM]) up to 0.2 m (digital ortho image/photo [DOP]) requires very large amounts of data, which is a major challenge when viewed across the federal state. For the federal states of North Rhine-Westphalia and Thuringia, a total of around 1 TB of height and spectral data is available along the area of the rail infrastructure. Due to the size of the data, a tile-by-tile processing is implemented within the tool. Thus, an unlimited number of data can be loaded within the sub-processes. The projection of the respective tile is used to assign matching and overlapping DSM, DTM, and DOP, which are calculated in sub-processes if necessary. The generated GIS tool also offers various sub-processes for data preparation, tree recognition and tree characterization,

which are explained in more detail in the following sections. The graphical user interface of the tool offers a large number of input options for the majority of the processes in order to ensure adaptation to different spatial conditions or data availability. The programming is based entirely on Python version 3.7, whereby the processing of raster data is based on the Geospatial Data Abstraction Library (GDAL) and the processing of vector data is based on the Simple Features Library (OGR). The graphic surface is designed with TKinter. An example of the GIS tool for filtering power lines can be found in Figure 1. The tools are integrated into ArcMap using the ArcGIS Addin Manager. With the help of the Addin Manager, individual toolbars can be created and functions can be assigned (Figure 1).

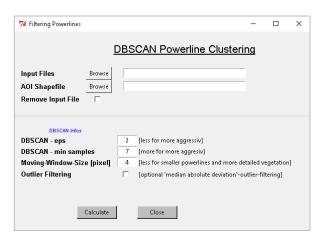


Figure 1: Graphical interface for filtering overhead lines.

3.2 Data acquisition

Elevation and spectral data are downloaded for tree recognition along the track network. This data is made up of 1 x 1 km of tiles statewide (Figure 2). In some cases, like the DTM data in North Rhine-Westphalia, these are combined into 2 x 2 km tiles. The uniform reference grid is part of the European initiative to set up a uniform spatial data infrastructure INSPIRE (BKG 2020). This basis of the uniform data structure enables the required data along the rail network to be downloaded automatically within the GIS tool for North Rhine-Westphalia and Thuringia. Components of the URL query for the automated download are derived from the reference grid (Figure 2). The query is se-

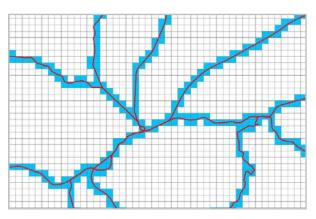


Figure 2: Reference grid for data download. Red: route network. Blue: relevant tiles for tree recognition.

lected on the basis of the existing route numbers of the track network. The graphical interface and functionality of the download-tool is implemented using C#.

3.3 Data preparation

The downloaded initial data from the federal states of North Rhine-Westphalia and Thuringia have different data formats which are harmonized for further processing. For this purpose, the freely accessible FU-SION program from the United States Department of Agriculture in Version 3.80 is used (MCGAUGHEY, 2018). In addition, North Rhine-Westphalia does not provide a direct DTM, so these are derived from the first return signals of the additionally downloaded LAZ data (McInerney & Kempeneers 2015). After the height data has been harmonized, the next step is to derive the normalized digital surface model (nDSM) (Figure 3), which is finally smoothed using a gaussian filter to avoid oversegmentation (MCGAUGHEY, 2018).

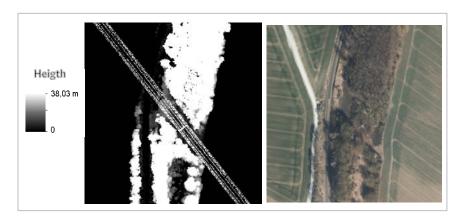


Figure 3: Power lines shown in the nDSM (left) and DOP (right).

In the next processing step, power lines are filtered within the derived nDSM. Experience has shown that these have a negative effect on the tree recognition accuracy and are difficult to differentiate spectrally (Figure 3). If trees are assigned, these may suggest a non-existent hazard due to the height and proximity of the track. CHI et. al (2019) were able to achieve success in the segmentation of power lines with density-based clustering (DBSCAN). Based on this, a methodology for filtering power lines is used within this project. After the observation area has been determined by Open Street Map (OSM) data or attributes of the freely accessible track network, height values over 5 m with a high spatial proximity are combined as a class with the help of the DBSCAN. For these points a median-moving-window-smoothing is performed. Finally, outliers can be filtered for remaining points.

3.4 Tree detection

In the approach implemented here, tree detection is carried out using the LM methodology. A virtual window of variable size moves over the nDSM and outputs all local maximum values (Figure 4). The WS method is then used for tree canopy delineation. For this method the nDSM is inverted and virtually filled with water. As soon as these virtual water basins connect or a height threshold is reached, the crown delineation is carried out (Figure 4). The result of this processing step is a shape file with tree top delimitations. Since this method makes delimitations on the basis of height values, an over-segmentation (e.g. infrastructure) can be assumed. Further adjustments will be made accordingly.

One parameter for better differentiation of treetop delimitations is, for example, the minimum height of the considered grid cells of the nDSM (KE & QUACKENBUSH, 2011). Thus, ground artifacts and inaccuracies

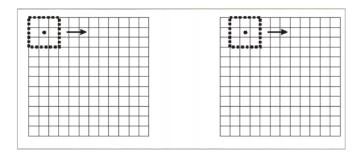




Figure 4: Tree recognition methodology. Left: Local-Maximum. Right: Watershed Segmentation.

of the height data can be excluded from the consideration already at 1 m. However, the GIS tool also allows this threshold value to be adjusted in order to possibly make regional adjustments. With the help of the previously downloaded DOP, trees are also differentiated based on their spectral reflectance value. Depending on the time of the flight, it is recommended to adjust the threshold value. When calculating the entire federal state, a threshold value of -0.2 is used in order not to exclude trees, for example, in the case of deciduous trees during winter flights or in the shadowy areas of houses. In addition to this spectral threshold, excluded and observation areas are used to better distinguish vegetation within the investigation area. The area under consideration is the track network buffered by 50 m, whereas exclusion areas can represent tunnels, OSM houses or the track network buffered by a few meters. The latter serves to better exclude the overhead lines from electrified tracks.

3.5 Tree characterization

In the next step, the identified individual trees can be assigned important tree and location properties in order to enable a potential hazard analysis. The respective information is determined from raster files of the corresponding attribute and geometric calculations. Growth modeling and hazard analysis are finally derived from the existing attributes. The assigned attributes are briefly discussed below

Tree height

The tree height results from the nDSM value of the local maximum within an identified treetop.

Distance to the rail network

Using the DTM, DSM and track network as a line shape file, the distance, i.e. the three-dimensional distance between the ground point of the height value of a tree and the closest point on the track, can be determined. The Z-value of the tree is taken from the data of the DTM and that of the track from the DSM. If the Z-value is adjusted by +5.35 m, the distance to overhead lines on electrified tracks can be calculated.

Recording date

As an essential component of growth modeling, the recording date of the DSM is required to put the data set in a temporal context. For the federal states considered in this project, the recording date of the surface models can be called up on the one hand by the META files of the file download (Thuringia), on the other hand by the WMS provided (North Rhine-Westphalia).

Growth modeling

For growth modeling, the Chapman-Richards growth function (RICHARDS 1959) was selected, which among the three-parametric functions is also the most widespread in the literature (PRETZSCH 2019). An estimated time series from the forest data store serves as the data basis. In order to reduce the model risk of underestimating the tree height, the 98 percentiles of the growth functions are used for the height development.

Topex

For the calculation of the Topex, the gradient angles within the specified distance in eight surrounding directions (N, NE, E, SE, S, SW, W, NW) are determined for each location within the DTM. These are then summed up and describe the susceptibility to wind in relation to the topography of the area (RUEL et al. 2002, MIKITA & KLIMÁNEK 2010).

Wind

The freely available wind data from the German Weather Service (DWD) are used to check the location's susceptibility to wind. These provide information about the mean annual wind speed at a height of 20 m with a spatial resolution of 200 m, based on the wind field model from 218 ground stations in Germany (DWD 2013).

Soil

In order to take the soil into account, freely accessible geodata from the Geological Service of North Rhine-Westphalia are used (IT-NRW, 2020). These include, among other things, information about the soil type at the site. According to MEYER (1988), the soil type is summarized in three risk categories for tree falls.

Tree species

Information on deciduous/conifer tree distinction could be derived using a supervised classification based on Sentinel-2 data. The basis for this is a knowledge-based selection of the reference data with the help of the Normalized Difference Vegetation Index (NDVI). Training- and validation areas can be derived from the freely accessible data of the High-Resolution-Layer-Forest, the Corine-Land-Cover data and the 'Digitales-Basis-Landschaftsmodell' (digitale landscape description of Germany - DLM).

Tree vitality

A method based on the Disease Water Stress Index (DSWI) according to GALVÃO et al. (2005) is used to assess tree vitality. This represents the loss of vitality based on changes in the leaf pigments and the leaf water content. This index is calculated at phenologically comparable points in time and then classified into change classes using a change vector.

Hazard analysis

The risk analysis is carried out in a two-stage process. First, the basic exposure of the rail network in terms of tree heights in relation to the distance to the track network is divided into 4 categories (Table 1).

TABLE 1: OVERVIEW OF COMMON GROWTH FUNCTIONS (PRETZSCH 2019).

Hazard	d class	Description of the class boundaries
1		Distance> current / future tree height with 2 m uncertainty range
2		Distance> current / future tree height without 2 m uncertainty area
3		Distance <current 6="" and="" free="" future="" height="" m="" outside="" td="" the="" tree="" zone<=""></current>
4		Distance <current 6="" and="" free="" future="" height="" m="" td="" tree="" within="" zone<=""></current>

In a second step, a hazard due to the extended exposure of a location is determined using suitable factors. While the basic exposure analysis only considers the tree height in relation to the distance to the track infrastructure, the extended exposure analysis includes the other properties and parameters listed above. The approach of Ordered Weighted Averaging (OWA) is used, according to which the measure of tradeoff and risk can be adjusted between the factors (JIANG & EASTMAN 2000). The value ranges of the incoming factors are standardized by fuzzification to the value range [0-1], with a fuzzy membership function being selected for each factor. The factors are then included with the same weighting. By defining sorted weightings, the factor values are sorted and weighted combined based on polygons.

4 Results

4.1 Visualization

As explained in the previous chapters, the individual tree detection is based on the high-resolution digital terrain and surface models. The results at the detailed level of the explained GIS tool process are exemplified in Figure 5. The figure shows the hazard classes of the basic exposure analysis. Each individual tree is thus evaluated according to its individual height and position in relation to the track infrastructure. The attributes and classifications of the extended exposure analysis are also available in the attribute table of each detected individual tree.

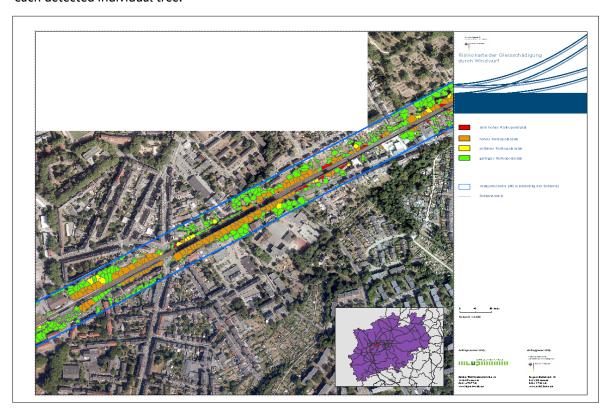


Figure 5: Observation area from route number 2160 in NRW.

In order to give users and interested parties a larger overview, not only detailed maps but also statewide hazard warning maps are created. Figure 6 shows an overview map of Thuringia for risk assessment. In this representation, the route network is buffered by 750 m for better visualization and divided into segments. Within the segments, the mean value of the basic exposure values for tree identifications is formed. For better informative value, the resulting mean values are standardized to a value range between 1 and 4. Figure 6 shows the exemplary representation of the overview map for Thuringia.

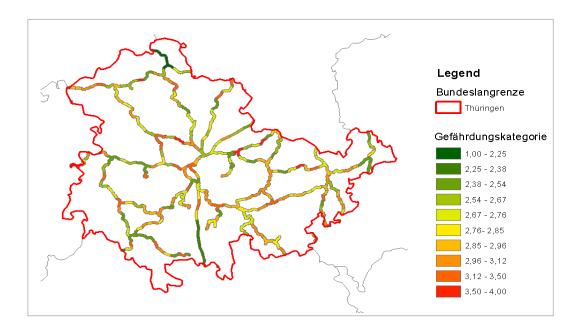


Figure 6: Overview map for the risk of windthrow in trees along the route network in Thuringia.

4.2 Validation of the results

4.2.1 Filtering power lines

Figure 7 shows that supra-regional power lines could be successfully removed due to the good coverage in the DSM (Figure 3, b and c). Problems arose, however, with the overhead lines of electrified railway tracks.

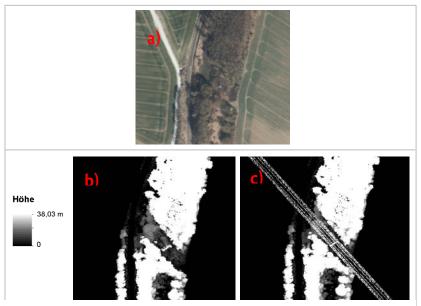


Figure 7: Filtering of the vegetation height grid using the DBSCAN a) DOP, b) results of the filtering, c) unfiltered nDSM.

4.2.2 Tree species classification

For the tree species classification described in Section 3.5, the grid values obtained from the reference data were divided into 70% training values and 30% validation values. The confusion matrix shown in Table 2 and the respective kappa coefficient were calculated from the validation data.

TABLE 2: VALIDATION OF TREE SPECIES CLASSIFICATION.

	North Rhine-Westphalia			Thuringia		
		Deci- duous	Conifer		Deciduous	Conifer
Confusion Matrix (pix)	Deciduous	4200	200	Deci- duous	4345	185
	Conifer	345	3980	Conifer	345	3980
Kappa coefficient		0.88			0.91	

Table 2 shows that there are more misallocations in conifers than in deciduous trees. Nevertheless, a large part of the tree population is classified correctly. This is supported by the resulting kappa coefficient and the increasing agreement of the classification as the kappa coefficient approaches 1 (COHEN 1960).

4.2.3 Tree recognition

For the validation of the tree identifications, over 1000 trees along the route network could be delimited from false-color images by interpreting aerial photographs. With a few exceptions, all trees could be identified (Table 3).

TABLE 3: VALIDATION OF TREE RECOGNITION.

	North Rhine-Westphalia	Thuringia	
Mapped trees	716	494	
Recognized trees	712	492	

The incorrect tree surveys are composed of the scenarios shown in Figure 8. At A) it should be added that the date of the DSM was taken on March 16, 2015, whereas the DOP of the aerial mapping is March 4, 2019. The unrecognized tree in Figure 8 B) can be traced back to the exclusion area of the bridge shapefile. In Figure 8 C), missing height data at the border area with Saxony are the cause of the lack of tree registration

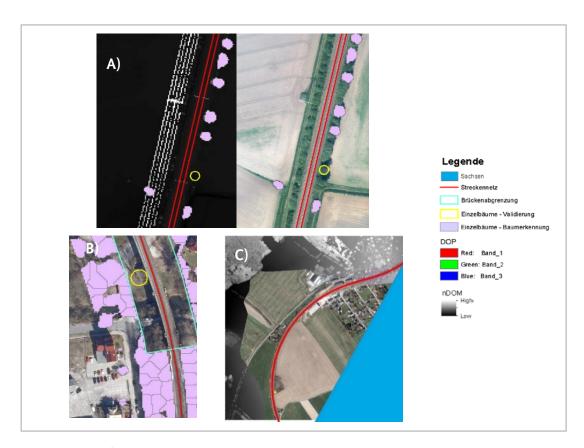


Figure 8: Causes of missing single tree recognitions.

5 Discussion

The aim of this research project, the development of a process chain for deriving trees along the German rail network, has been successfully accomplished for the federal states of North Rhine-Westphalia and Thuringia. The data acquisition is implemented with an automated download using URL-Queries. The extent to which this approach can be adopted for other federal states cannot be conclusively clarified due to the different data provision within the project in the individual federal states. However, the script could easily be adapted to various freely accessible URL download requests.

In addition to data acquisition, the focus of the project was on an automated process chain with the implementation of a GIS tool in order to enable repeatability in other areas. The entire coverage of the applied methodology in Python and its simple design of graphic interfaces confirm their functionality for processing geographic information. The individual processes of the GIS tool were batched to derive trees from North Rhine-Westphalia and Thuringia. The state-wide tree population could thus be recorded with uniform parameters.

However, this approach of a nationwide tree recognition method also leads to some limitations and inaccuracies that could be analyzed in more detail in further investigations and possibly weakened by regional and spatially adapted approaches. For the overall calculation of both federal states, an NDVI threshold of -0.2 was used, for example, in order not to exclude any deciduous trees in the non-leaved state. In addition, small buffers were chosen around the track network and OSM houses so that nearby vegetation is not excluded. This sometimes leads to over-determination of tree recordings or confusion with infrastructure. However, the demonstrably low incidence of missing tree records is positive (Table 3). Within the performed validation, these could only be detected sporadically in erroneous data of the peripheral areas, far-reaching flight times and too large exclusion areas. Accordingly, an individual consideration of route sections with the help of the GIS tool seems to be reasonable. Adjustments of the parameters can be made to the flight period, track position and other conditions.

It should be noted that the reference data come from mostly dense, large-scale forest areas. However, linear tree structures often occur near the track, which can lead to problems with classification and vitality grids with a resolution of 10 m and thus affect the hazard analysis.

6 Summary

Trees along the German route network represent a high-risk potential. Within this research project, trees were recorded with the help of freely available geodata and their risk potential was assessed. Therefore, a process chain was developed and the repeatability of the methodology was ensured by integration within a GIS tool. The implementation of the method by Python underlines its functionality.

The hazard analysis developed within the scope of this project represents an approach to assessing the track network with regard to windthrow. This allowed distinctions to be made between tree stands in terms of their spatial position in relation to the track network and in terms of their hazard potential. With the help of the generated overview maps of the federal states of North Rhine-Westphalia and Thuringia, a tool was also generated to better assess the high number of recognized trees within a federal state and to identify special danger areas. Thus, the results confirm the potential of freely available geospatial data. The validation results of the identified individual trees and the tree species classification verify this. However, validations of the risk analysis, growth modeling and overdetermination of tree could not be adequately investigated within this project. This represents approaches for additional research questions. In the future, a partial consideration of route sections for the derivation of trees and their hazard potential is recommended. Endangered sections of the route could be recalculated retrospectively by adjusting individual parameters such as the flight period, the track position or other conditions.

7 Figures

Figure 1: Graphical interface for filtering overhead lines.	9
Figure 2: Reference grid for data download. Red: route network. Blue: relevant tiles for tree recognition	9
Figure 3: Power lines shown in the nDSM (left) and DOP (right).	10
Figure 4: Tree recognition methodology. Left: Local-Maximum. Right: Watershed Segmentation	11
Figure 5: Observation area from route number 2160 in NRW.	14
Figure 6: Overview map for the risk of windthrow in trees along the route network in Thuringia	15
Figure 7: Filtering of the vegetation height grid using the DBSCAN a) DOP, b) results of the filtering c) unfiltered nDSM	_
Figure 8: Causes of missing single tree recognitions.	17

8 Tables

Table 1: Overview of common growth functions (PRETZSCH 2019)	13
Table 2: Validation of tree species classification.	16
Table 3: Validation of tree recognition	16

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