Mapping of the vulnerability of forest resources due to extreme winter storms in the state of Baden-Württemberg in Germany

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ABSTRACT: Forestry is of paramount importance to the state of Baden-Württemberg, as it supplies wood resources for material and energetic use, and plays a central role in energy transition, climate protection, etc. On the other hand, Baden-Württemberg has been and will might be hit by extreme winter storms that significantly damage the forest resources and wildlife habitat, as well as roads and infrastructure. Such storms may occur with greater intensity and more frequently than before, which might cause increased associated costs. This paper investigates the vulnerability of the forest resources due to extreme winter storms. At first, a detailed literature review on wind effects on trees, factors associated with storm damage, modelling approaches, etc. are performed. The empirical Weight of Evidence (WofE) model is found to be a suitable approach to analyze the vulnerability of forest resources. Different steps associated with this approach are systematically described; multiple model outcomes are evaluated and validated in order to justify the acceptance of the posterior probability maps of the vulnerable forest areas in Baden-Württemberg. In this regard, 11 different models with varying combinations of predictor variables (evidence themes) are tested to understand the most important variables.

The most significant WofE-model (M8) identifies that the soil type, forest type, topographic exposure in the direction of west and gust wind speed greater than 35 m/s are the most important determinants in windthrow assessment. It produces a raster grid with cells in a one ha unit area representing the posterior probabilities of damage due to a stochastic winter storm for approximately 14 million ha of forests in the state of Baden-Württemberg. About 18% of the forest area is identified as highly vulnerable, whereas 20% of the area lies within the moderately vulnerable areas. However, the majority of the forests (62%) are within the lowest vulnerable areas. In terms of spatial patterns, the forests towards the west - where topographic exposure values are high, soil is acidic and forests are coniferous - are mostly vulnerable.

Such mapping can help private and public forest owners and decision makers to identify whether and how much of their forest is vulnerable. They can plan appropriate forest management and salvage operation strategies to reduce the overall economic impacts immediately after occurrence of an extreme storm.

KEYWORDS: Forest resources, Vulnerability, Extreme winter storms, Weight of evidence, GIS

Introduction

A standing forest provides a wide variety of direct and indirect benefits to society. Some benefits, e.g., climate protection or biodiversity benefits are even external to the nation where the forest is located. It is a source of life for society and environment, as it plays an important role in maintaining the balance of the ecosystem. Human beings are both directly and indirectly facilitated with this private and social benefits of forestry and its diverse services. The direct advantages of having stocks of trees in forests are many, e.g., standing trees are seen as capital goods or assets that are invested for long term. Many forest dependent industries, e.g., paper and pulp, sawmills, pellets and wood chips industries, biomass based power plants directly get raw materials (i.e., wood) from the forests. The indirect economic benefits of forests are also important. Many positive ecosystem services delivered by the forests to society, e.g., the cleaning up of ground water, protection of settlement from natural disasters, provision of wildlife habitats, allowance of the biodiversity that amass from the forest, the ability to absorb carbon dioxide (CO_2) to stop global warming is extremely important to society.

Within a changing climate, hydro-meteorological natural hazards continue to strike and are expected to increase in magnitude, complexity, frequency and, therefore, impact many parts of the world (Murshed et al., 2007). Compared to other geophysical (earthquake, tsunami, etc.), hydrological (flood) or climatological (extreme temperature, drought, etc.) events, extreme winter storms affect relatively large areas and cause considerable losses, often amounting to several billion Euros. Winter storms caused an estimated 2.3 billion US$ of insured losses in 2014, up from 1.9 billion US$ in 2013. From 1994 to 2013 winter storms resulted in about 27 billion US$ in insured catastrophic losses (MunichRe, 2015). In central Europe, the storm Kyrill in January 2007 caused insured losses exceeding 4 billion Euros, at least 46 fatalities and uprooted more than 60 million trees (Fink et al., 2009). Lothar and Martin storms in December 1999 in Europe, caused 19.2 billion US$ of damage to power grids and forest resources. Windstorm Klaus in January 2009, was responsible for around 40 million of m³ of damages in the south-western part of France (Nicolas, 2009). Other winter storms, e.g., Wiebke and Vivian in 1990 also caused significant forest damage.

In Europe, over the period of 1950 – 2000, an annual average of 35 million m³ wood was damaged by forest disturbances and storms were responsible for 53% of the total damage (Schelhaas et al., 2003). In Germany, 75% of economic losses related to natural disasters from 1970 to 1998 can be attributed to storms, mostly occurring in winter (MunichRe, 1999). In Baden-Württemberg, climate and weather related disturbances and damages are also systematically assessed and recorded (ForstBW, 2014). It is reported that the current high level of storm activity will not drop considerably in future decades over southern and central Germany (Rauthe et al., 2010).

Therefore, the main objective of this research is to systematically map the vulnerable forest areas in the state of Baden-Württemberg so that the private and public forest owners and decision makers can identify whether and how much of their forest is vulnerable. They can plan appropriate risk management, forest management and salvage operation strategies to reduce the overall economic impacts immediately after occurrence of an extreme storm.

In Chapter 2, a detailed literature review on wind effects on trees, factors associated with storm damage, modelling approaches, etc. are carried out. The required data and methodological approaches are described in Chapter 3. Then Chapter 4 illustrates the key research findings. Finally, a conclusion and research outlook are drawn in Chapter 5.

Literature review

The **wind effects on trees** can induce windthrow, a situation when a tree is uprooted or broken at the trunk due to wind. Two distinct types of windthrow are defined based on the frequency of occurrence and magnitude of damage. Catastrophic windthrow refers to infrequent (e.g., 20 year return period) storms with remarkably strong winds which cause severe damage to both stable and unstable tree stands (Gardiner et al., 2010). The main factors causing this type of windthrow are wind speed and direction, as well as local topographic conditions, which makes it difficult to predict. Endemic windthrow occurs more frequently (e.g., 1-5 year return period) and is caused by trees having a low stability and increased exposure due to recent harvesting or thinning, making them more vulnerable to recurring peak winds (Lanquaye, 2003). This research aims to analyze catastrophic windthrow.

In **assessing storm damage**, (Jiao-jun et al., 2004) reviewed the publications of three international conferences on 'wind and trees' e.g., (Coutts and Grace, 1995), (Peltola et al., 2000) (Ruck et al., 2003) and identified the needs for further research in the fields of wind damage to natural forests, research regarding the management for wind-damaged forests, etc. Recently, (Schindler et al., 2012) also reviewed the research progress in wind-tree interactions by highlighting the International Conference on 'Wind Effects on Trees'. They also summarized the research gaps regarding the interaction of high impact wind and trees at a local scale, the interaction between high-impact winds and complex forest structure, etc. (Hanewinkel et al., 2011) also summarized 35 papers to review the most important factors in assessing storm damage. This research considers the suggestion made by previous studies.

According to former research, **factors influencing the vulnerability** of forests to winter storms can be divided into four groups: (a) weather, (b) site conditions, (c) topographic conditions and (d) tree and stand characteristics (Schindler et al., 2009). The main factors associated with windthrow can be described in three levels of detail: (a) individual tree, (b) forest stand and (c) site level. At each level, the factors influence differently. For example, at tree level, factors such as height, crown size and rooting structure are important. At the stand level, common variables include species composition, height, density and silviculture treatments. At the site level, soil conditions and topographic exposures are assessed for their contribution to, or correlation with, windthrow damage. This research will focus on the vulnerability assessment at the stand and site level.

Wind damage vulnerability **modelling approaches** are dependent on the type of windthrow under investigation. Three main categories of vulnerability modelling approaches are identified in related literature (M. Hanewinkel et al., 2011): expert system, mechanistic and empirical/statistical approaches. They have advantages and disadvantages, depending on the scale and extent of study area, objectives and forest structures. Considering these aspects, an empirical approach is proved suitable for the forests in Baden-Württemberg.

Empirical approaches reveal the correlation between the occurrence of wind damage (i.e., the dependent variable) and in some cases the magnitude of damage, to a number of independent variables including tree, stand and site characteristics as well as meteorological data (Schindler et al., 2012). Such models calculate the probability of damage, given the presence or absence of the most statistically significant variables. A statistical model such as the Weights of Evidence (WofE) method is particularly suitable for large regions and heterogeneous forest structures. The forest stands of Baden-Württemberg - having a complex and variable structure as well as a very heterogeneous topography and soil compositions - justify WofE as the most suitable method (Hanewinkel et al., 2010).

In a GIS-based estimation of winter storm damage probability, (Schindler et al., 2012) tested a number of predictor variables for their significance in the weight of evidence model, concluding that soil type and moisture, geology, forest type, topographic exposure and gust fields greater than 35 m/s were the most important factors available for assessing damage probability at the state level. The authors stated that CORINE land cover data was crucial for the analysis given that important tree and stand level data were unavailable.

Several limitations were observed in previous studies. For example, complex wind field was not considered, the winter storm occurrences data was used from the one dataset only and the analysis was performed at a gross (e.g., 5 ha) resolution. This research aims to improve the mapping of the vulnerability of forest resources in term of methods, input data and level of analysis (discussed in Chapter 3).

Methodological approach

Definition

Weights of Evidence follows the Bayesian theorem to calculate posterior probability of an event or occurrence, which is simply a prior probability updated to account for the presence of certain evidentiary knowledge. This method provides the statistical framework to quantify the strength of spatial association between training data sets (e.g., windthrow occurrence) and evidence themes (e.g., forest type, soil acidity, wind speed, etc.).

This method was applied in different fields of research, e.g., windthrow vulnerability (Schindler et al., 2012), wildfire risk (Romero-Calcerrada et al., 2008), mineral prospectivity (Carranza, 2009), etc. The mathematical explanation of WofE method was described in all these literatures and therefore, are not explained here.

Mapping windthrow vulnerability

The WofE modelling approach suggested by (Schindler et al., 2009; Schindler et al., 2012) is improved to create windthrow vulnerability maps in the state of Baden-Württemberg. For this purpose, the forest land cover data at 30 metres resolution is used. These datasets provide an additional class for windthrow damaged areas which were not considered by previous studies. Moreover, these land cover datasets significantly increase the number of training points, since the minimum detection size for windthrow is less than one ha, which was five ha in earlier studies. The stochastic extreme winter storm hazard data is collected at a 1 km x 1 km grid for different return periods (Hofherr and

Kunz, 2010) and thus enables modelling considering complex wind fields and at a higher spatial resolution than in previous studies.

In this research, a total number of 3,221 training points are derived from LUBW 2000 and CLC 2000 damage class datasets under the condition that the damage areas are greater than one ha. Furthermore, 11 evidence themes covering weather, site, topography and forest conditions are considered. Then the significance of these themes is tested through formulation of multiple models in order to understand the important factors influencing the development of WofE modelling. Finally, the WofE method has been applied to create posterior probability maps to predict the windthrow vulnerability.

The methodology proposed by (Agterberg et al., 1993) within the framework of Spatial Data Modeller for ArcGIS and Spatial Analyst is applied in this study. The general workflow of the methodology is illustrated in Figure 1.

Figure 1: Description of the WofE methodology

Step 1 and 2 - Identify and harmonize evidence themes: The forest evidence theme originates from the LUBW 1993 land cover dataset containing three classes for the forest type (i.e., deciduous, coniferous and mixed forest). The site evidence layers include datasets of soil type, moisture content, acidity and geology, which are derived from the Water and Soil Atlas of Baden-Württemberg. The topographic variables used in this study include elevation, slope, aspect, and distance limited topographic exposure (TOPEX) indices. The mean wind speed data of (Hofherr and Kunz, 2010) is the weather related evidence theme.

In total, 11 evidence themes having a different number of classes are considered in the development of WofE model. An overview of all these themes along with the original number of classes are described in Table 1.

Table 1: List of evidence themes and corresponding number of classes

Evidence groups	*Evidence themes*	*Original number of classes*
Forest	Forest type	3
Site	Soil type	29
	Soil moisture content	21
	Soil acidity	13
	Geology	14
Topography	Elevation	Continuous
	Slope	Continuous
	Aspect	Continuous
	Distance Limited TOPEX (Sum of 8 distance limited TOPEX grids)	Continuous
	Modified distance limited TOPEX indices (8 grids for each cardinal direction)	Continuous
Weather	Wind speed	Continuous

These evidence themes and training points are collected in different spatial scales and resolutions. They were harmonized to the same spatial resolution, format and scale.

Step 3 - Calculate weights and generate statistics: In this step, weights and other statistics for each class of an evidence theme is formulated, e.g., in order to understand the spatial association and to measure the uncertainty associated with the statistics. Spatial association between training points and classes of evidential themes are measured by weights and contrasts. Contrast, C, is the difference between positive (W+) and negative (W-) weights for each class within the evidence layer and represents an overall measure of the spatial association between the training points and the evidence class. The final weights reveal the predictive capability of each class.

Step 4 - Reclassify evidence themes: The statistics generated in the previous step provide parametric measures for generalizing and reclassifying evidence into binary and multi-class themes. The results of the weight and other statistics of the most significant themes are illustrated tables. For example, concerning soil acidity, damage is strongly associated with 'strong and deep acidic soil near moderately acidified soil' (class 11), Soils with higher moisture content exhibit different levels of association with damage. The most significant soil moisture class is 'fresh to temporarily fresh soils' (class 14). Soils of lower moisture content are generally negatively associated with damage. Soil type also proved to be an important variable, e.g., soil class 'the sand and clay mixture alternating with loam over clay' (class 203) shows strong association with storm damage.

The continuous topographic themes, e.g., elevation, aspect and slope showed little association with damage patterns, whereas the distance-limited TOPEX to the west (TOPEX_W) show a greater association with damage. This can be explained by the observation that the main direction of the wind from extreme storm is westerly (Heneka, 2006; Schmidt et al., 2010), and the forest areas exposed to this direction are likely to experience stronger winds.

Regarding forest type, a strong association between the coniferous forest class and the wind damage training points are revealed. Conversely, both deciduous and mixed forests show a strong negative association with damage training points.

In literature, a widespread damage has been associated with wind gust speeds over 35 m/s (Schindler et al., 2009), (Schindler et al., 2012), therefore, a binary layer representing mean gust speeds greater than this speed is created. This layer however shows a relatively weak association with damage.

Step 5 - Calculate response: In this step, continuous scale posterior probability maps are prepared. The first map on the model 1 (M1) is produced from the selected 8 evidence themes and their associated weights. A statistical summary of all the models (M1 – M11) is given in table 2. Since the posterior probability maps do not consider the conditional independence among layers, further steps are required to ensure that evidence layers are not redundant.

Step 6 - Assess conditional independence: 11 models are created to find out the best combination of evidence themes with the greatest conditional independence (CI) and highest accuracy; these models are presented in the Table 2 with statistics provided to evaluate CI within the response maps. CI test is performed considering 'Overall Omnibus test' and Agterberg-Cheng (AC) test (Schmitt, 2010).

The Agterberg-Cheng (AC) test is the most reliable CI test (Schmitt 2010). Here probability values greater than 95% or 99% indicate that the hypothesis of CI should be rejected, but any value over 50% indicates some level of conditional dependence (Schmitt, 2010). Among the 11 models, the maximum probabilities exist in models M1 - M7 and they are not CI (as the probability is 1), while the models M8 - M11 show the minimum CI (see Table 2).

Finally, the overall CI value is prepared by rescaling the AC test from 0% - 100% which indicates the confidence whether the posterior probability is conditionally independent. For example, models M1 - M7 show 0% confidence that the posterior probability is CI, while M8, M9, M10 and M11 display approximately 16%, 4%, 28% and 68% confidence on CI, respectively.

Therefore, the CI tests performed in this step prove the acceptance of the models M8, M9, M10, M11. However, for certain tests, some of these models perform better than others, e.g., M11 apparently shows best results, since the differences between the calculated and observed windthrow occurrences (T-n) is minimum (20.70), conditional independence (CI) ratio is maximum (0.99), only 66% probability that model is not CI, and 68% confidence that the posterior probability is CI (see Table 2). But the validation of these models needs to be performed in order to justify and to accept one particular model and the corresponding posterior probability map.

Table 2: The statistical summary of different models

Model name	Predictor themes used*	Observed windthrow TPs (n)	Expected windthrow occurrences(T)	T-n	CI ratio (n/T)	AC test (T-n/σT)	Prob that model is not CI	Overall CI	AUC
M1	A, D, F, G, L, M, S,T	3221	6348.5	3127.5	0.51	31712519	1	0	0.74339
M2	A, F, G, L, M, S,T	3221	5409.7	2188.7	0.6	28610808	1	0	0.718925
M3	A, F, G, L, S,T	3221	4711.6	1490.6	0.68	22118812	1	0	0.709826
M4	A, F, G, L, M, T	3221	4092.9	871.9	0.79	16.885.709	1	0	0.716252
M5	F, L, M, S, T	3221	3569.1	348.1	0.9	8.818.192	1	0	0.693819
M6	A, F, G, L, T	3221	3731.9	510.9	0.86	9277636	1	0	0.715049
M7	A, F, L, M, T	3221	3503	282	0.92	6.159.362	1	0	0.710749
M8	A, F, L, T	3221	3295.2	74.2	0.98	1.415.498	0.922	0.157	0.705947
M9	F, L, S, T	3221	3311.9	90.9	0.97	205.169	0.98	0.04	0.688526
M10	G,F, L, T	3221	3270.4	49.4	0.98	1.071.215	0.858	0.284	0.696946
M11	F,L,M,T	3221	3241.7	20.70	0.99	0.419119	0.662	0.675	0.676524

*Here A is soil acidity, D is elevation in 6 classes (35-270, 270-420, 420-560, 560-720, 720-900, 900-1480 metres above sea level), F is forest type, G is geology, L is the gust wind speed > 35 m/s, M is soil moisture, S is soil type, and T is distance limited TOPEX for compass direction west. M8 is selected as the most significant model.

Step 7 - Model validation methods: Several validation methods, e.g., Success-Rate Curve, Prediction-Rate Curve and Blind Tests are performed to build confidence in the WofE model outcome (Schmitt, 2010). For example, the Success-Rate Curve (SRC) test provides a measure of how well a model predicts known windthrow damage of training points. For visual inspection, a success-rate curve is created by plotting the cumulative training points (%) on the y axis and the cumulative area (%) on the x axis. The area under the curve (AUC) gives an indication of the predictive accuracy of the model. Among the best performing CI tests of models M8 – M11, M8 displays the maximum AUC of 70.5%. Therefore, considering the accuracy and different CI tests performed in earlier steps, M8 is the most reliable model. It considers four predictors, e.g., soil acidity, forest type, TOPEX west and wind gusts greater than 35 m/s.

Step 8 - Classification of posterior probability map: The posterior probability values are ranged from 0 (min) to 1 (max). They should be interpreted as relative ranking of wind damage potential. (Fabbri and Chung, 2008) suggested to replace these values by classifying in ranks; they proposed methods to interpret and classify them, e.g., using a Cumulative Area Posterior Probability (CAPP) curve (Schmitt, 2010).

The classification of the final model (M8) is performed by plotting the cumulative area (%) vs. the posterior probability. Break points are selected where the curve rose sharply indicating significant change between probabilities classes. Three classes are defined and the breaks at 0.0022 and 0.0045 are selected as the class threshold. In the highest vulnerable class, approximately 18% of the forest is located whereas in the medium and low vulnerable class, about 20% and 62% of the forest is identified, respectively.

Finally, the classified posterior probability map of windthrow vulnerability (M8) with the least CI and highest accuracy is displayed in Figure 2. A careful visual inspection and GIS overlay reveal that the areas with high topographic exposure to the west, acidic soils and coniferous forest types exhibit highest damage probabilities.

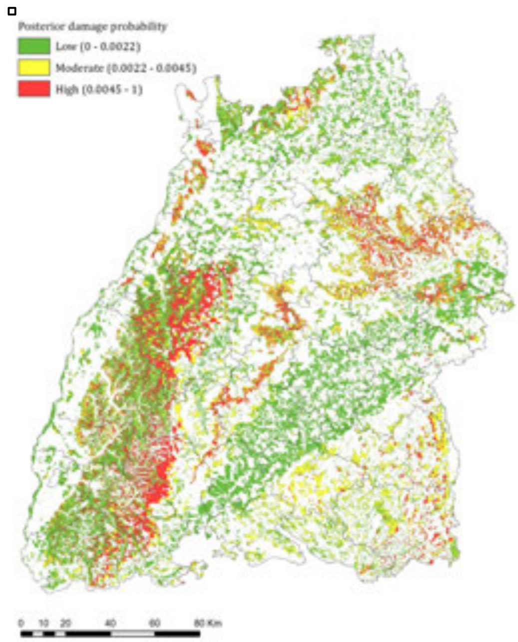

Figure 2: Posterior probability of damage due to an extreme winter storm

Discussion of results

The weight of evidence methodology produced raster grids of one ha unit area representing the posterior probabilities of damage due to a stochastic winter storm. The prior probability of the grids is updated to posterior probability by summing all weights from each of the evidence themes (logits converted into probability) at the grid location.

Posterior probabilities are calculated for approximately 14,035,596 ha of forests in the state of Baden-Württemberg. A classification based on CAPP reveals that the majority of the forests (62%) are located within a low damage class, while the moderate damage probability class covers 20% and the highest damage probability class covers 18% of the area (Figure 3).

The posterior probability map depicts a similar damage pattern as in the actual LUBW and CLC damage data (highest damage in northern Black Forest and the eastern districts of Heidenheim and Ostalbkreis), with the highest proportions of forest in the high damage class located in the northern Black Forest and stretching eastward. A significant exception to these results is found in the southern portion of the Black Forest in the districts of Schwarzwald-Baar-Kreis and Breisgau-Hochschwarzwald, where the model predicts high damage probabilities, but very low proportions (< 1%) of total forests that might be actually damaged (as observed in LUBW and CLC damage data); this can be identified in the lower right example in Figure 4. This signifies that the area is highly vulnerable to future extreme winter storms.

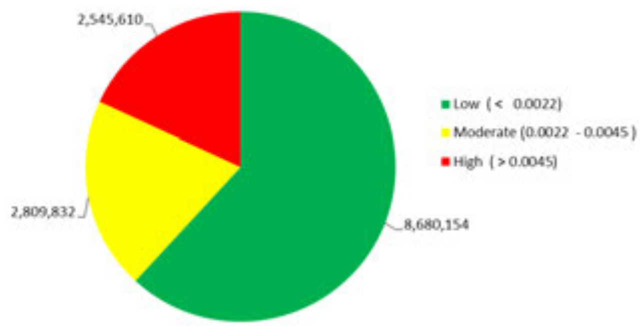

Figure 3: Share of low, medium and high vulnerable forest areas

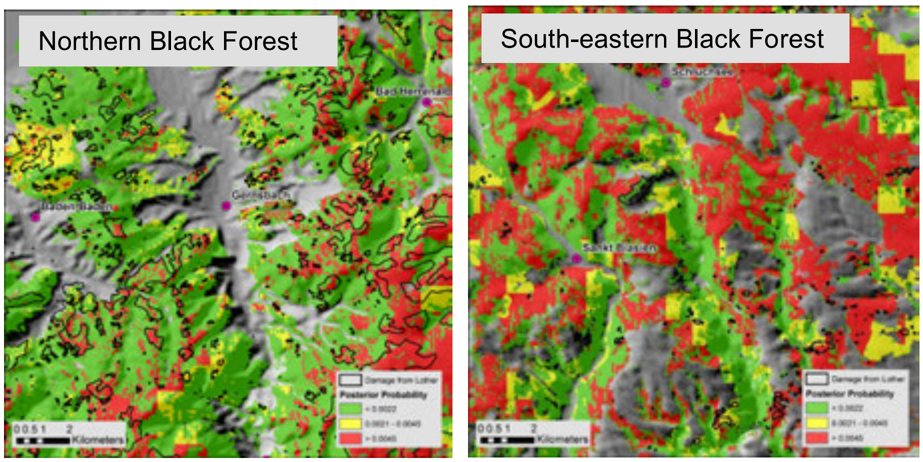

Figure 4: Examples of WofE results in Baden-Württemberg: northern Black Forest (left), southeastern Black Forest (right)

Conclusions

The mapping of the vulnerable forest areas across Baden-Württemberg at one ha resolution is meant to provide scientists and policy makers with a state-wide perception of probable damage patterns of different magnitudes considering the present conditions. With the delineation of such vulnerable areas, further economic impacts can be analysed and evaluated, e.g., by considering typical post storm forest and salvage (windthrow) management practices, as well as by developing alternative policies and scenarios (Murshed and Werner 2016).

Many limitations do however exist in the WofE modelling approach. Simulated wind speeds do not prove to be a significant predictor in the model. This is in agreement with other studies which have investigated windthrow damage in central Europe (Schindler et al., 2012). The severity of damage also depends on the duration of the event, maximum sustained wind speed and precipitation immediately prior and during the event (Mitchell, 2012). Therefore, further investigation on understanding the interaction of these factors over the duration of a storm is required. WofE method can be further improved by considering more detailed classification of evidence themes, e.g., soil types or tree species

The area under curve (AUC) gives an indication of the predictive accuracy of the model. For the final model (M8) considered in this research, the AUC was 70.5%, which is slightly lower (72.8%) than that found in the study of (Schindler et al., 2012). They tested a number of predictor variables for their significance in the model, concluding that soil type and moisture, geology, forest type, topographic exposure, and gust fields greater than 35 m/s were the most important factors available for assessing damage probability at the state level.

This research assumes a stochastic winter storm which affects all the districts in Baden-Württemberg. But in reality, the extent of the storm might be smaller or vice versa. For example, Lothar affected some regions in Baden-Württemberg, especially in the Black Forest, but not the whole of Baden-Württemberg. Therefore, future research could focus on smaller regions and inspect the vulnerability with higher resolution of data. For example, forest establishment data, which contains detailed tree and stand information for the public forests in Baden-Württemberg, can be explored.

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