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Because of some land-use practices (such as overstocking with wild ungulates, historical clear-cuts for mining, and locally persisting forest pasture), protective forests in the montane vegetation belt of the Northern Limestone Alps are now frequently overaged and poorly structured over large areas. Windthrow and bark beetle infestations have generated disturbance areas in which forests have lost their protective functions. Where unfavorable site conditions hamper regeneration for decades, severe soil loss may ensue. To help prioritize management interventions, we developed a geographic information system-based model for assessing sensitivity to site degradation and applied it to 4 test areas in the Northern Limestone Alps of Austria and Bavaria. The model consists of (1) analysis of site conditions and forest stand structures that could increase sensitivity to degradation, (2) evaluation of the sensitivity of sites and stands, and (3) evaluation and mapping of mountain forests' sensitivity to degradation. Site conditions were modeled using regression algorithms with data on site parameters from pointwise soil and vegetation surveys as responses and areawide geodata on climate, relief, and substrate as predictors. The resulting predictor–response relationships were applied to test areas. Stand structure was detected from airborne laser scanning data. Site and stand parameters were evaluated according to their sensitivity to site degradation. Sensitivities of sites and stands were summarized in intermediate-scale sensitivity maps. High sensitivity was identified in 3 test areas with pure limestone and dolomite as the prevailing sensitivity level. Moderately sensitive forests dominate in the final test area, Grünstein, where the bedrock in some strata contains larger amounts of siliceous components (marl, mudstone, and moraines); degraded and slightly sensitive forests were rare or nonexistent in all 4 test areas. Providing a comprehensive overview of site and forest stand structure sensitivity to site degradation, our sensitivity maps can serve as a planning instrument for the management and protection of mountain forests.

Keywords: Spatial modeling; site parameters; soil; stand parameters; stand structure; sensitivity mapping; decision support; vulnerability assessment.

Introduction

The mountain forests of the Northern Limestone Alps provide varied functions and ecosystem services. They deliver drinking water, improve air quality, allow recreation, produce timber and fuelwood, protect against avalanches and rockfall, conserve soil, and control floods. They also harbor high biological diversity and provide habitats for endangered species. However, mountain forests are fragile ecosystems, which have to be managed and utilized carefully to maintain their functionality (Andersson et al 2000; Kräuchi et al 2000; Brang et al 2006).

Large areas of the mountain forests in the Northern Limestone Alps are characterized by naturally unfavorable conditions for tree growth (Englisch 1991). In the montane and subalpine vegetation belts, weathering of pure limestone and dolomite often leads to shallow, stony, and nutrient-poor soils with low water storage capacity (Baier 2004; Ewald 2005). These unfavorable site conditions are often connected with high relief, strong altitudinal and slope gradients, high solar radiation on sun-exposed slopes, and strong variation of weather conditions.

Past forest management also affects the current condition of mountain forests in the area. Overaged and

FIGURE 1 Disturbance area in the Höllengebirge (Upper Austria). The 2007 windthrow hit highly sensitive forests and initiated processes of site degradation with severe loss of humus, nutrients, and soil and a strong decrease in water storage capacity. (Photo by Klaus Katzensteiner)

uniform stands with sparse canopy cover are frequently found in large areas of the montane vegetation belt of the Northern Limestone Alps as a result of excessive clear-cutting by the mining industry, clearing of forest pasture and subsequent afforestation with Norway spruce in past centuries, and overstocking with wild ungulates, a practice which is still ongoing (Bernhart and Knott 1986; Katzensteiner 2003; Prietzel 2010). Historically, management favored the dominant Norway spruce over other tree species. Because of browsing by deer and chamois, the stands often do not regenerate naturally.

Thus, because of unfavorable site conditions and land use, the mountain forests of the Northern Limestone Alps are often poorly structured, which puts their protective functions at risk in the long run (Prietzel 2010), as well as other ecosystem services, such as providing clean drinking water.

Natural hazards and calamities such as windthrow and bark beetle attack have, during the past decade, led to the local loss of forest stability and protective functions. After a disturbance, site degradation starts with severe loss of nutrients, organic matter, and mineral soil, followed by a decrease in water storage capacity (Figure 1; Kohlpaintner and Göttlein 2009; Katzensteiner 2011;

Hollaus et al 2013; Mayer et al 2014). These difficult conditions can hamper regeneration and establishment of new forests for decades (Pröll et al 2014).

In order to prioritize management interventions to counteract these problems, we developed a geographic information system (GIS)-based model for assessing sensitivity to site degradation and applied it to 4 test areas in the Northern Limestone Alps. The model consists of (1) analysis of site conditions and forest stand structures that could increase sensitivity to degradation, (2) evaluation of the sensitivity of sites and stands, and (3) evaluation and mapping of mountain forests' sensitivity to degradation.

Study area

The study area comprises the western part of the Northern Limestone Alps, a mountain range in the eastern Alps covering 11,880 km^2 in Bavaria (Germany) and Vorarlberg, Tyrol, Salzburg, Upper Austria, and Styria (Austria). The Northern Limestone Alps are naturally covered by montane mixed deciduous–coniferous forests with Norway spruce (*Picea abies* [L.] H.

FIGURE 2 Location and topography of the 4 test areas.
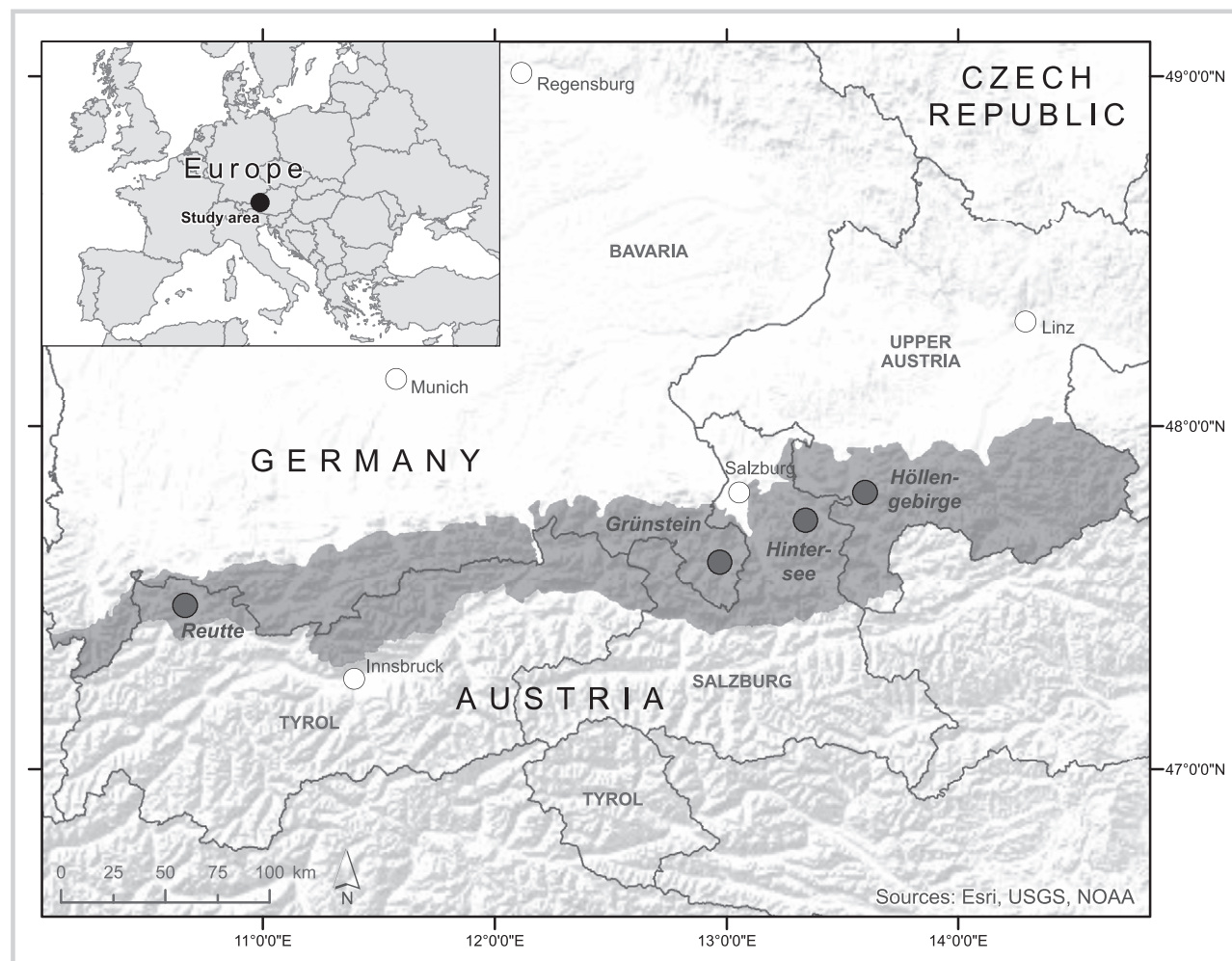
Karst.), European beech (*Fagus sylvatica* L.), and silver fir (*Abies alba* Mill.), and subalpine *Picea abies* forests above 1400 m. Within the western part of the Northern Limestone Alps, we analyzed 4 test areas representing the west–east climatic gradient across the mountain range (Figure 2).

The test area Reutte (47°29′39″N to 47°31′32″N; 10°38′16″E to 10°40′55″E) is located in northwestern Tyrol (Austria) and covers 11.56 km². It is characterized by a strong altitudinal gradient with altitudes between 830 and 2163 m above sea level, a cold and moist climate with mean annual temperature ranging from 6.1°C at lower elevations to −0.5°C at the summit, and annual precipitation of 1376 mm (climate station Reutte; data provided by Zentralanstalt für Meteorologie und Geodynamik, www.zamg.ac.at). Dolomite and limestone are the main soil-forming parent materials (substrate map obtained from Amt der Tiroler Landesregierung, Abteilung Forstplanung, 2013). The forest stands are spruce forests or spruce-dominated mixed forests with

silver fir, European beech, and sycamore maple (*Acer pseudoplatanus* L.) (Pröll et al 2014).

The test area Grünstein (47°34′46″N to 47°36′11″N; 12°57′14″E to 12°59′35″E) covers 7.66 km² in southeastern Bavaria (Germany). In an elevation gradient between 570 and 1380 m, the climate is cool and humid with mean annual temperatures from 7.5°C in the valley to 4°C on the ridges and annual precipitation ranging from 1275 to 1990 mm (Hera et al 2012). The area is formed of calcareous sedimentary rocks such as pure limestone and dolomite, but also siliceous limestone, mudstone, and marly moraines from the last ice age (Kolb 2012). Tree species composition was strongly altered in favor of Norway spruce and European larch since the early Medieval period by the use of timber for salt mining.

The test area Hintersee in Salzburg (Austria; 47°43′42″N to 47°45′55″N; 13°14′41″E to 13°17′34″E) covers 14.76 km² at altitudes between 680 and 1360 m; mean annual temperatures range from 7.6°C in the valley to 4.2°C at the top; and annual precipitation is 1430 mm

(climate station St. Wolfgang; data provided by Zentralanstalt für Meteorologie und Geodynamik). Particularly dolomite, but also limestone are the main soil-forming parent materials (geological map for Salzburg obtained from Geologische Bundesanstalt, Pestal et al 2005). The forest stands are mixed forests with spruce, silver fir, and European beech or spruce forests. In 2007, an area of about 0.15 km^2 of the tree layer was uprooted by a windstorm.

The fourth test area (47°47′12″N to 47°48′50″N; 13°33′40″E to 13°37′26″E) is part of the Höllengebirge in Upper Austria with an area of 14.26 km^2. The altitude ranges from 490 to 1590 m; mean annual temperatures range from 8°C at lower elevations to 3.6°C at the subalpine elevation belt; and annual precipitation is about 1830 mm (climate station Feuerkogel; data provided by Zentralanstalt für Meteorologie und Geodynamik). The soil-forming parent material is dominated by limestone at higher elevations in the northern part of the test area and dolomite at lower elevations in the southern part (geological map for Upper Austria obtained from Geologische Bundesanstalt, Krenmayr and Schnabel 2006). The forest stands in the Höllengebirge are dominated by Norway spruce, European beech, and silver fir and intermixed with sycamore maple and European ash (*Fraxinus excelsior* L.). The forests were subject to windthrows with subsequent bark beetle attacks in 2007 and 2009 (Mayer et al 2014). About 0.30 km^2 of the tree layer was blown over or broken.

Sensitivity assessment

Assessment of sensitivity to site degradation consisted of 3 steps: analysis of individual site- and stand-structure-related parameters, evaluation of site and stand sensitivity, and evaluation of forest sensitivity to degradation (Figure 3).

Site analysis

In order to detect naturally unfavorable site conditions for tree growth, we performed a site analysis with the following parameters as proxies for water and nutrient availability in the rooting zone:

- *Effective soil thickness* is defined as the depth of the organic layer and the mineral soil, corrected by the proportion of skeletal soil components (ie particle diameter > 2 mm).
- *Water storage capacity* is a general measure of the amount of water available in soils for plant growth.
- *Average nutrient value*, indicating the supply of nitrogen, phosphorus, and potassium, is calculated as the un-weighted average of the Ellenberg indicator values for nutrients (Ellenberg et al 2001) of the species recorded within a vegetation plot.

- *Soil type*, using the Food and Agriculture Organization's soil classification (eg Lithic Leptosols, Rendzic Leptosols, chromic Cambisols, and Cambisols; FAO 2006), is defined by a characteristic sequence of horizons with specific chemical, physical, and biological properties.
- *Humus form* (eg mull, moder, mor, and tangel) is defined as the part of the topsoil that is strongly influenced by organic matter and coincides with the sequence of organic and underlying organo-mineral horizons (Zanella et al 2011). The humus form indicates the thickness of soil organic matter, which is of crucial importance for productivity, forest vitality, and important ecosystem services because of its function as a rooting zone and nutrient supply as well as its water storage capacity at shallow skeletal sites (eg Prietzel and Christophel 2014).

To analyze these site parameters, we developed statistical models that related site parameter data from pointwise soil and vegetation surveys as *responses* (also referred to as dependent or explained variables) with geodata on climate, relief, and substrate as *predictors* (also referred to as independent or explanatory variables). Soil-related values were derived from 1616 georeferenced morphological soil profile descriptions recorded within the entire western mountain range of the Northern Limestone Alps and stored in soil inventory databases (eg WINALPecobase [for details, see Reger et al 2012]; ID EU-DE-003 in the Global Index of Vegetation Plot Databases [Dengler et al 2011]). Nutrient values were derived from 1551 vegetation data points recorded in the field and stored in vegetation databases with georeferenced vegetation plots (eg WINALPecobase).

Predictor variables were preselected for their potential relevance to forecast soil properties. In order to avoid multicollinearity, we only used predictors with a Spearman correlation of 0.7 (Fielding and Haworth 1995). The set of predictors includes 5 topography-related variables and 2 substrate-related variables (Table 1). Climatic conditions were indirectly considered by using the topographic variables elevation and transformed slope aspect as proxies for temperature, precipitation, and radiation. All topographic variables were derived from digital elevation models (DEMs) with 10 m resolution for Bavaria (obtained from Bavarian Surveying Administration), Tyrol (Land Tirol, data.tirol.gv.at), Salzburg (SAGIS), and Upper Austria (Amt der Oberösterreichischen Landesregierung) using Spatial Analyst tools in ArcGIS 10.2.1 ESRI Inc., 2014). Chemical and physical properties were derived from substrate maps for Bavaria (Kolb 2012) and Tyrol (Amt der Tiroler Landesregierung, Abteilung Forstplanung) and from geological maps for Salzburg and Upper Austria (Geologische Bundesanstalt). Geological units were translated into Kolb's (2012) substrate classification system. In addition to the topography- and substrate-

FIGURE 3 Approach to assessing sensitivity to site degradation.
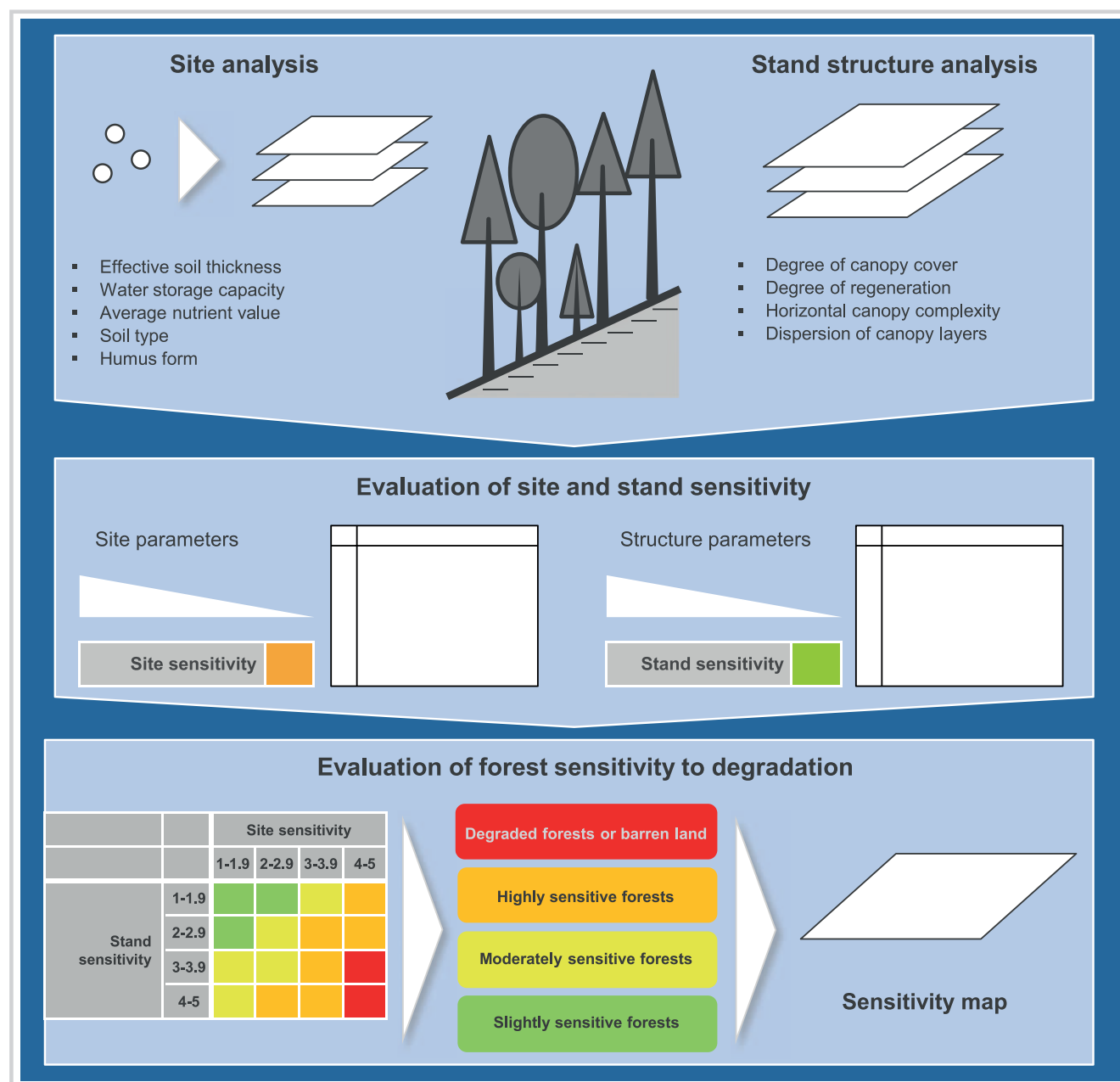
related effects, we considered spatial effects by including easting and northing in the statistical modeling.

Soil parameter–environment relationships were modeled using generalized additive models (GAMs) for continuous response variables and random forests (RFs) for categorical response variables. GAMs (Hastie and Tibshirani 1990), provided by the package mgcv (Wood 2006) available within the R software version 3.1.0 (R Core Team 2014), are nonparametric extensions of generalized linear models, which make it possible to fit response curves with nonparametric smoothing

functions instead of parametric terms. We used penalized regression splines and the model distribution family Gamma with the log link function due to positive-valued response variables. Smoothness was optimized based on generalized cross validation (Wood 2006). We allowed higher complexity only for the spatial effect (Paciorek 2009) to represent the spatial autocorrelation of the data.

In order to achieve more parsimonious models, we applied a backward variable selection procedure, removing variables from the full model on the basis of

TABLE 1 Predictor variables for the statistical modeling of the site parameters.

Variable		Reference
Topography	Elevation (m)	Digital elevation model
	Slope inclination (°)	Digital elevation model
	Transformed slope aspect (folded around thermal optimum)	Beers et al (1966), Reger et al (2011)
	Curvature	Zevenbergen and Thorne (1987)
	Compound topographic index	Beven and Kirkby (1979)
Substrate	Chemical properties of bedrock (carbonate gradient)	Kolb (2012)
	Physical properties of bedrock (weathering gradient)	Kolb (2012)

variable significance estimations. To assess the relative importance of the different explanatory variables in the models, relative variable importance was calculated from the range of the categorical or smooth effect (ie maximum effect to minimum effect; see Mellert and Ewald 2014).

The range of the categorical or smooth effect for all predictor variables of each model was scaled to sum up to 100, with higher values indicating stronger influence on the response variable. Model performance was assessed by the percent of deviance explained and the adjusted R^2.

TABLE 2 Final statistical models of the site parameters.

Statistical model	Predictors (variable importance)	Model performance
Effective soil thickness (cm) (generalized additive model)	Slope inclination (36.0%) Chemical properties of bedrock (29.8%) Elevation (22.6%) Physical properties of bedrock (11.6%)	Adj. R^2: 0.371 Expl. deviance: 34.7% Generalized cross-validation score: 0.28922 n: 1616
Water storage capacity (mm) (generalized additive model)	Chemical properties of bedrock (38.8%) Slope inclination (27.9%) Elevation (12.6%) Compound topographic index (11.4%) Physical properties of bedrock (9.3%)	Adj. R^2: 0.458 Expl. deviance: 42.7% Generalized cross-validation score: 0.32196 n: 1441
Average nutrient value (generalized additive model)	Elevation (32.8%) Chemical properties of bedrock (23.3%) Curvature (11.3%) Slope inclination (9.9%) Compound topographic index (7.8%) Transformed slope aspect (7.5%) Physical properties of bedrock (7.4%)	Adj. R^2: 0.468 Expl. deviance: 49.3% Generalized cross-validation score: 0.02417 n: 1556
Soil type (random forest)	Chemical properties of bedrock (46.8%) Physical properties of bedrock (32.2%) Slope inclination (12.2%) Elevation (2.9%) Compound topographic index (2.6%) Transformed slope aspect (2.5%) Curvature (0.8%)	Accuracy: 58.0% Kappa: 0.38 Out-of-bag error: 54.4% n: 1603
Humus form (random forest)	Physical properties of bedrock (32.1%) Elevation (25.2%) Slope inclination (14.7%) Chemical properties of bedrock (13.2%) Compound topographic index (7.7%) Curvature (4.2%) Transformed slope aspect (2.9%)	Accuracy: 66.4% Kappa: 0.38 Out-of-bag error: 54.3% n: 1599

Validation was performed by a 10-fold cross-validation procedure with 10 random data splits into test and training data at the splitting rate of 1:10.

RFs (Breiman 2001) are an ensemble method, in which many different classification trees are combined to produce a more stable and accurate classification. Within the RF implementation, we applied conditional inference trees as base learners, which were implemented with the function cforest() in the package party available within the R software version 3.1.0 (Hothorn et al 2006; R Core Team 2014). The splitting in recursive partitioning in conditional inference trees is based on significance tests of independence between any of the predictors and the response. The classification predictions are made on a majority vote using the predicted probabilities for the present site parameters in order to assign the class with the highest probability (Strobl et al 2009). The results of the classification models are response classes. The predictive performance of the RF models was assessed on those observations that were not included in the learning sample for a specific decision tree (ie observations that were not part of the bootstrap sample of the original data set). Those out-of-bag observations provided independent test samples for computing prediction accuracy. The relative importance of the predictor variables was calculated by the permutation accuracy importance measure included within the varimp function in the party package. This measure is estimated by comparing the prediction accuracy before and after randomly permuting the values of a particular variable.

The final statistical models with predictors and model performance are presented in Table 2. These were used to predict and map the site parameters for the 4 test areas. The spatial implementation of the site parameters was done with the help of the R-package raster (Hijmans et al 2013) in R software version 3.1.0 (R Core Team 2014), resulting in 10-m-resolution site parameter maps.

Stand structure analysis

Stand structure plays an important role in site protection. Uneven and multilayered forest stands with a mix of sizes and age classes are assumed to be best suited to protect their sites against processes such as excessive soil erosion and debris flows (eg Ott et al 1997; Kräuchi et al 2000; Motta and Haudemand 2000). Stand structure analysis makes it possible to differentiate well-structured from poorly structured forests. We assessed forest stand structures in the 4 test areas based on the following parameters:

- Degree of canopy cover is defined as the proportion of the area covered by the canopy of trees and shrubs with a height ≥2 m. This threshold was used to exclude bushes, ground vegetation, and rocks from the analysis. A high degree of canopy cover contributes to soil protection by increasing interception and reducing surface runoff (Ammer et al 1995; Führer and Nopp 2001).
- Degree of regeneration specifies the proportion of the canopy cover made up of established regeneration with saplings of 2 m to 5 m height in order to assess the horizontal regeneration structure of the forest stands. Regeneration below the main canopy cover is not considered. Adequate regeneration improves forest resilience (see Wehrli et al 2007).
- Horizontal canopy complexity counts the number of layers with a canopy cover ≥20%. We differentiated 4 layers with heights of 2–5 m (established regeneration), 5–10 m (lower layer), 10–25 m (intermediate layer), and ≥25 m (upper layer) in order to assess the stands' horizontal structure.
- Dispersion of canopy layers was calculated as the number of canopy layer patches and gap patches (<2 m) within the area divided by the maximal possible number of canopy layer patches within the area.

The stand structure parameters were derived from crown height models (CHMs), which provide horizontal information on canopy height. The CHMs were obtained by subtracting DEMs derived from last-pulse laser airborne scanning data and digital surface models (DSMs) derived from first-pulse laser airborne scanning data (for details on laser scanning and its application in forestry, see eg Koch et al 2008). The DEMs and DSMs were obtained with a resolution of 1 m for Reutte from Land Tirol (data.tirol.gv.at), for Grünstein from Bayerisches Landesamt für Vermessung und Geoinformation (data acquired from 2008 to 2009, http://vermessung.bayern.de/) and processed by ZEBRIS Geoinformationssysteme und Consulting (http://www.zebris.com/), for Hintersee from SAGIS (http://www.salzburg.gv.at/sagis/), and with a resolution of 0.5 m for Höllengebirge from Amt der Oberösterreichischen Landesregierung (data acquired in 2012, https://www.land-oberoesterreich.gv.at/).

We developed GIS-based models within the model builder framework of ArcGIS 10.2.1 ESRI, Inc., 2014, using block statistics and resampling techniques in order to derive the horizontal stand structure parameters from the CHMs. Analysis resolution for all stand parameter models was 10 m × 10 m, corresponding to the resolution of the site parameters.

Evaluation of site and stand sensitivity

Site and stand structure characteristics were evaluated for their sensitivity to site degradation. The evaluation used an approach developed to classify protective forests according to their protection performance (see Göttlein et al 2009, 2011). Site and stand characteristics were classified in 5 sensitivity levels from "very low" to "very high" (Tables 3 and 4). The cutoff values for the classes corresponded to the classifications reported in different

TABLE 3 Site parameters with sensitivity levels and weightings.

Site parameter	Sensitivity level					Weighting
	Very low (1)	Low (2)	Medium (3)	High (4)	Very high (5)	
Effective soil thickness (cm)	>120	60–120	30–60	15–30	<15	×4
Water storage capacity (mm)	>180	120–180	90–120	30–90	<30	×2
Average nutrient value	>6.3	5.7–6.3	4.45–5.7	3.5–4.45	<3.5	×2
Soil type	Stagnic Cambisols/ Fluvisols	Chromic Cambisols	Rendzic cambic Leptosols	Rendzic Leptosols	Lithic Leptosols	×3
Humus form	Mor/tangel	Moder	Mull	Tangel (on rendzic Leptosols)	Initial humus	×3

studies dealing with these parameters (see AK Standortskartierung 2003; Kobler 2004; Göttlein et al 2009, 2011; Ewald et al 2013). The sensitivity levels of the parameters were multiplied by specific weights (Tables 3 and 4) depending on their relevance to the sensitivity assessment (see Göttlein et al 2009).

To assess stand and site sensitivity, the evaluation tables were applied to the modeled site and stand parameters. Site and stand sensitivity levels were calculated as the sum of the weighted sensitivity levels of the site parameters divided by the sum of weightings. Resulting values were divided into 4 sensitivity levels: low (1–1.9), moderate (2–2.9), high (3–3.9), very high (4–5). Forests above 1600 m were not evaluated, as stand structure differs from that of montane mixed forests at lower elevations.

Evaluation of forest sensitivity to degradation

In order to evaluate forest sensitivity to degradation, we combined site and stand sensitivity levels within a matrix (Figure 3) based on the assumption that highly sensitive site conditions can be partially compensated by good stand structure. This made it possible to map mountain forests according to their sensitivity to site degradation. The sensitivity levels were as follows:

- Degraded forests and barren land;
- Highly sensitive forests;

TABLE 4 Stand structure parameters with sensitivity levels and weightings.

Stand structure parameter	Sensitivity level					Weighting
	Very low (1)	Low (2)	Medium (3)	High (4)	Very high (5)	
Degree of canopy cover	≥0.9	0.8–0.9	0.7–0.8	0.5–0.7	<0.5	×9
Degree of regeneration	>0.7	0.5–0.7	0.3–0.5	0.1–0.3	<0.1	×3
Horizontal canopy complexity	≥3	2	1	1 (>80%)	0	×2
Dispersion of canopy layers	>0.2	0.15–0.2	0.1–0.15	0.05–0.1	<0.05	×2

- Moderately sensitive forests;
- Slightly sensitive forests.

Results

Figure 4 shows the mapping of sensitivity to site degradation for the 4 test areas. Degraded forests and barren land were identified in the Reutte test area. They consisted of very shallow sites with severely reduced water storage capacity and nutrient supply. Often, these areas included deforested ecosystems. Highly sensitive forests were widely distributed in all 4 test areas, particularly in areas that have been prone to windthrow like the Höllengebirge. These forests are not degraded but characterized by a high site sensitivity with low soil thickness, water storage capacity, and nutrient supply. The forest stands are often monolayered with a sparse canopy cover and a low degree of regeneration. Moderately sensitive forests were identified in all 4 test areas. They included forests with low site-related sensitivity but very high stand-related sensitivity, high site-related and low stand-related sensitivity, and moderate sensitivity related to both sites and stands. Slightly sensitive forests were particularly identified in the Grünstein test area. Within these forests, we found at least moderate site sensitivities combined with well-structured forests or low site sensitivities combined with a moderately developed stand structure.

Discussion

Forest management implications

Identifying forests' sensitivity to degradation can help forest managers prioritize interventions. Regeneration of degraded forest sites and establishment of new forests are often hampered for decades by poor conditions for rejuvenation and tree growth and may require extremely costly technical measures. Highly sensitive forests urgently need action to minimize or prevent further loss of organic matter, soil, and nutrients by providing cover and biomass (eg Christophel et al 2014). Such forest stands on shallow calcareous soils have also been found to be most vulnerable to climate warming due to expected increasing drought stress, productivity losses, and increased susceptibility to disturbances (Seidl et al 2011). The main objective of management strategies should be to restore these forests, which may require temporary snow barriers to shelter plantings.

Depending on the prevailing combination of site and stand structure conditions, management treatments in moderately sensitive forests should aim to improve site conditions by humus accumulation (eg by leaving tree residue in place) and/or to enhance stand structure by selective thinning and facilitation of regeneration, in all cases accompanied by adapted hunting management

and, where necessary, by planting. In slightly sensitive forests, the primary objective of management strategies is to maintain favorable stand structure and site conditions.

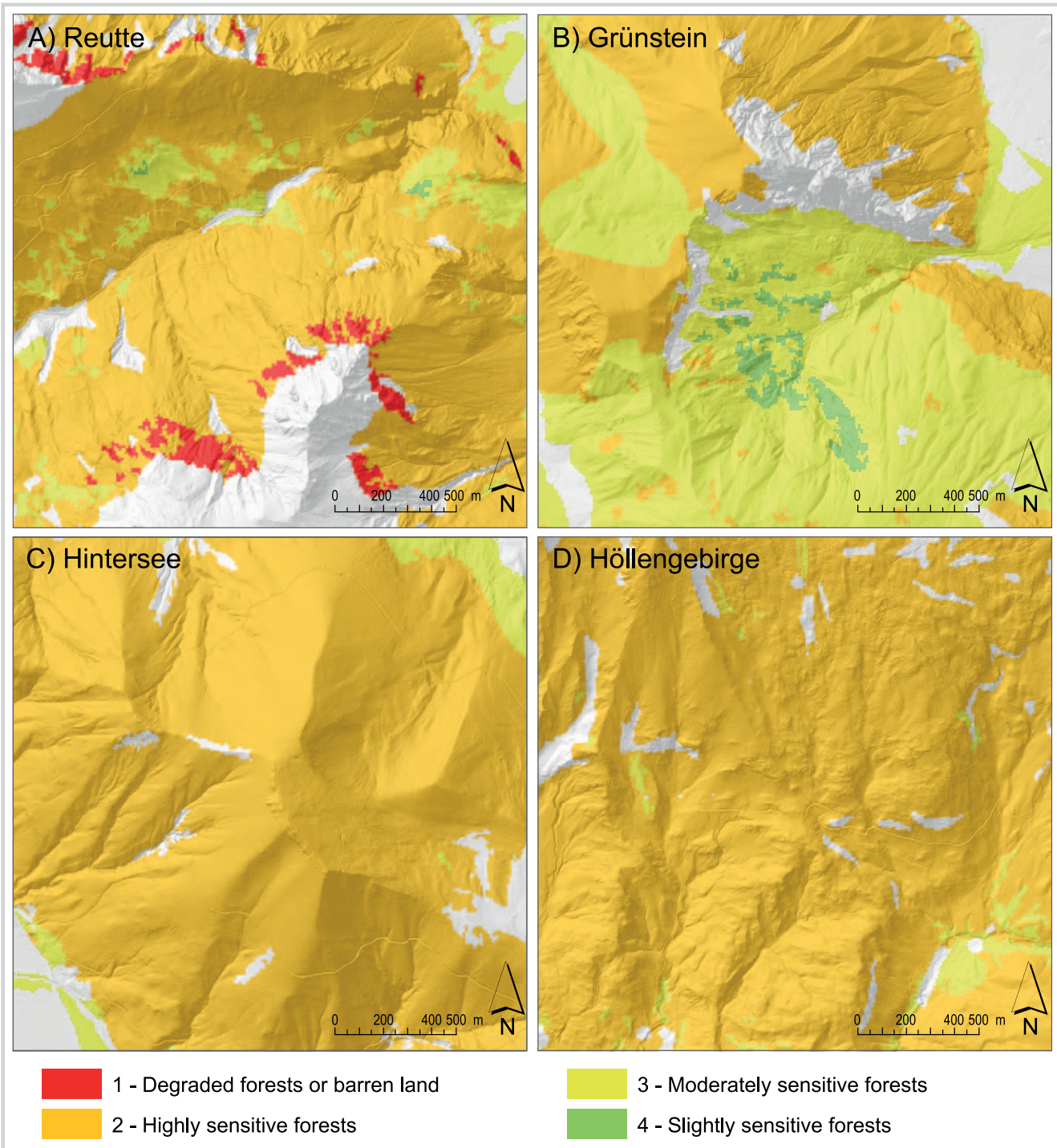### Sensitivity assessment approach

In this study, we proposed a sensitivity assessment approach that identifies and evaluates the sensitivity of mountain forests to site degradation. In this sense, our approach differs from the conceptual framework of vulnerability assessment defined within the report of the Intergovernmental Panel on Climate Change (IPCC), which additionally considers the exposure, impacts, and adaptive capacity of a system (Füssel and Klein 2006).We combined data sets and techniques of predictive soil mapping and remote sensing that are well established in spatial modeling.

Predictive soil mapping (also known as digital soil mapping) is widely used to assess soils and soil properties (McBratney et al 2003; Häring et al 2012). We used regression and classification techniques (GAMs and RFs) that have the potential to provide meaningful predictions outside the study areas if the environmental conditions are very similar. This produced promising GAMs for effective soil thickness, mean nutrient value, and water storage capacity and RFs for soil type and humus form. With an explained deviance between 34.7% and 49.3% or an accuracy of 58% and 66.4%, the models performed remarkably well, and the environmental predictors used showed ecologically reasonable partial effects.

Mellert and Ewald (2014), who regionalized nutrient values of vegetation to assess site fertility in mountain forests in the Bavarian Alps, used similar predictors (altitude, transformed aspect, slope, topographic wetness index, chemical properties of bedrock, ratio of thickness of organic layer to thickness of humic topsoil, clay content, and gravel content) and achieved an explained deviance of 53%. The performance of predictive soil models is highly dependent on the accuracy and availability of geodata. DEMs and the topographic indices calculated from them are often used in predictive soil mapping, as topography is one of the fundamental soil-forming factors (eg Seibert et al 2007).

Advances in remote sensing have made it possible to produce DEMs with finer resolutions than, for example, applied geological and substrate maps with scales from 25,000 to 200,000. Such maps provide information on the physical and chemical properties of the parent material, which are considered fundamental soil-forming factors in predictive soil mapping. Geological maps from different sources were unified to a comparable legend. It must be assumed that the superior predictive performance of topographical compared to petrographical predictors in our models is mostly due to the higher resolution of the former data layers, rather than to the higher importance of topography for soil formation. In that sense, our

FIGURE 4   Sensitivity of mountain forests to site degradation in sections of the 4 test areas.

A) Reutte

B) Grünstein

C) Hintersee

D) Höllengebirge

1 - Degraded forests or barren land

2 - Highly sensitive forests

3 - Moderately sensitive forests

4 - Slightly sensitive forests

empirical predictions are typical data-driven models, with error levels dependent on the scale of available geodata. Modeling performance could be further improved by integrating the degree of human impact (eg deforestation and pasturing) on soil conditions. However, areawide data indicating human impact are rarely available.

Remote-sensing techniques have recently been used to improve the efficiency and accuracy of forest inventories (McRoberts and Tomppo 2007). Stand structure analysis depends heavily on high-resolution remote-sensing data on crown height. The quality of laser scanner data is influenced by the point density of the scanning. Canopy height based on laser scanning data can be underestimated (eg Naesset et al 2004; Cashmer et al 2006). Underestimation is usually greater for cone-shaped trees (eg spruce) than for sphere-shaped trees (Koch et al 2008). However, laser scanning data with a high point density provide reliable height estimations even in leaf-off conditions (Rönnholm et al 2004). We used information from laser scanning data, which are often used in forest structure characterization (eg Naesset 2007; Hollaus et al 2009). Alternatively, DSMs derived from digital aerial images (eg Straub et al 2012) or high-resolution satellite data (eg Straub et al 2013) can also be used in combination with laser scanning DEMs to calculate crown height. The calculated CHMs provide horizontal information on the canopy cover. However, the vertical structure (eg results of regeneration) under the cover of mature trees remains hidden from analysis. Furthermore, the integration of tree species composition would improve the analysis of stand sensitivity.

Sensitivity assessment was conducted on an intermediate scale limited by the availability of geodata, yet corresponding to the scale of management decision-making in forest management, as postulated in the context of several studies pointing to the relevance of assessing sensitivity at the regional or landscape scale (O'Brien et al 2004; Lundmark et al 2008).

Conclusions

Our intermediate-scale sensitivity maps provide a comprehensive overview of site-related and stand-structure-related sensitivity to site degradation. Highly sensitive forests were identified as prevailing, particularly due to high site-related sensitivity (low soil thickness, water storage capacity, and nutrient supply). Using predictive soil mapping and remote-sensing techniques, our proposed approach can supplement traditional forest inventory and has 4 advantages:

- Its rules for sensitivity assessment are explicit and repeatable.
- It can be updated when new information (eg on tree species composition) becomes available and modified to further fields of application that rely on areawide site and stand structure information.
- Results are comparable within the study area, allowing forest managers to prioritize actions to support an efficient and focused allocation of limited resources.
- Because of its relatively simple data sets and techniques, it is transferable to other mountain areas with similar conditions (eg environmental gradients and inventories) and adequate data for site and structure analysis.

Sensitivity maps may serve as a forest management planning instrument at the regional level. Their support for adequate proactive forest management strategies may be of particular practical use in forestry. The intermediate scale of the maps corresponds to the scale of decision-making in forest management. However, for the management of mountain forests at a more detailed level, human expertise is still needed. The maps can also be implemented in regional forest information systems (eg Bayerisches Waldinformationssystem [BayWIS], Tiroler Raum-Informationssystem [tiris]). Thus, this approach offers a useful supplement to traditional forest inventories.

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