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ARTICLE

Emerging Technologies

Using machine learning on tree-ring data to determine the geographical provenance of historical construction timbers

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Abstract

Dendroclimatology offers the unique opportunity to reconstruct past climate at annual resolution and wood from historical buildings can be used to extend such information back in time up to several millennia. However, the varying and often unclear origin of timbers affects the climate sensitivity of individual tree-ring samples. Here, we compare tree-ring width and density of 143 living larch (*Larix decidua* Mill.) trees at seven sites along an elevational transect from 1400 to 2200 m asl and 99 historical tree-ring series to parametrize state-of-the-art classification models for the European Alps. To achieve geographical provenance of the historical series, nine different supervised machine learning algorithms are trained and tested in their capability to solve our classification problem. Based on this assessment, we consider a tree-ring density-based and a tree-ring width-based dataset for model building. For each of these datasets, a general not species-related model and a larch-specific model including the cyclic larch budmoth influence are built. From the nine tested machine learning algorithms, Extreme Gradient Boosting showed the best performance. The density-based models outperform the ring-width models with the larch-specific density model reaching the highest skill (f_1 score = 0.8). The performance metrics reveal that the larch-specific density model also performs best within individual sites and particularly in sites above 2000 m asl, which show the highest temperature sensitivities. The application of the specific density model for larch allows the historical series to be assigned with high confidence to a particular elevation within the valley. The procedure can be applied to other provenance studies using multiple tree growth characteristics. The novel approach of building machine learning models based on tree-ring density features allows to omit a common period between reference and historical data for finding the provenance of relict wood and will therefore help to improve millennium-length climate reconstructions.

KEYWORDS
artificial intelligence, dendrochronology, dendroprovenancing, European Alps, Extreme Gradient Boosting, *Larix decidua*, tree-ring density, tree-ring width

INTRODUCTION

The ability of computers to learn on the basis of existing data (machine learning [ML]) bears great potential to improve various scientific fields including bio- and geoscience (Jordan & Mitchell, 2015; Keitt & Abelson, 2021). In tree-ring research, ML has recently been applied for modeling stem diameter growth and vessel lumen or for climate reconstruction purposes (Bodesheim et al., 2022; Jevšenak & Skudnik, 2021; Ou et al., 2019; Salehnia & Ahn, 2022). In the (paleo)climatological context, tree-rings are an essential source to reconstruct past climate fluctuations beyond the instrumental period. Classical approaches consider the relation between climate elements (e.g., temperature or precipitation) and a tree-ring proxy, for example, tree-ring width (TRW) or maximum latewood density (MXD), by scaling or building linear regression models (Briffa et al., 1992; Cook et al., 2019; Cook & Kairiukstis, 1990; Esper et al., 2005, 2012; Gurskaya et al., 2012; Lara et al., 2020; Li et al., 2012; Wilson & Luckman, 2003). ML algorithms are tested as transfer functions for this relationship by training artificial neural networks, random forests, or boosted regression trees (Gu et al., 2019; Jevšenak et al., 2018; Jevšenak & Skudnik, 2021; Salehnia & Ahn, 2022).

Besides a robust growth-climate model, multi-centennial reconstructions rely on dead wood to extend living chronologies into the past. These samples are often collected from local historical construction wood of unknown origin (Büntgen et al., 2005; Hartl et al., 2022; Klippel et al., 2020; Labuhn et al., 2016; Liu et al., 2009; Schweingruber, 1988; Tegel et al., 2010; Wilson et al., 2005). The determination of the origin of ancient wood, the so-called dendroprovenancing, is a frequently applied tool to reconstruct trade and transportation routes (Bonde et al., 1997; Daly & Tyers, 2022; Linderholm et al., 2021; Shindo & Claude, 2019; Wazny, 2002), to uncover illegal logging (Kagawa & Leavitt, 2010), and determine the origin of artwork or shipwrecks (Bridge, 2011; Brookhouse et al., 2021; Domínguez-Delmás et al., 2020; Haneca et al., 2005). Classic approaches in dendroclimatology and -archaeology consider the correlation of series from unknown origin to a set of existing reference tree-ring chronologies (Bonde, 1992; Bridge, 2012). It is argued, however, that this classical dendroprovenancing with chronologies not always serves the complexity in the relationship between tree growth parameters and regionality (Bridge, 2000, 2012; Domínguez-Delmás et al., 2020; Drake, 2018; Haneca et al., 2005).

The application of ML is likely suitable for a probable higher complexity in this relationship. Approaches have been tested with different tree-ring proxies using multiple regression models (Dittmar et al., 2012; Wilson et al., 2004), or the ML algorithms k-nearest neighbor (kNN) (Gut, 2018), principal component analysis (PCA) (Wilson & Hopfmueller, 2001), or principal component gradient analysis (PCGA) (Akhmetzyanov et al., 2020; Buras et al., 2016). While PCGA and PCA rely on a common period of overlap between living and historical series for determining the provenance, Dittmar et al. (2012) used features of individual tree series to build a nonlinear regression model. However, many published approaches in dendroprovenancing generally lack basic ML model development steps like testing different algorithms and hyperparameter combinations before opting for a fitting algorithm. The a priori requirement of a common period between historical samples and a reference for effective dendroprovenancing remains the greatest challenge. The potential of additional parameters such as MXD or species-specific disturbance features (such as insect outbreaks) has so far not been tested in ML provenance models.

Dendroclimatological studies focus on regions, where tree growth is limited by a dominating factor, for example, the temperature at latitudinal or elevational tree line sites (Babst et al., 2013; Briffa et al., 1988; Esper et al., 2016; Hartl et al., 2021, 2022; Liu et al., 2009; Ljungqvist et al., 2020; Schneider et al., 2015; Wilson et al., 2016). Consequently, the quality of a tree-ring-based climate reconstruction derived from living and historic wood hinges on the consistency of the signal strength across the proxy sources, as the temperature signal of trees fades with decreasing elevation (Babst et al., 2013; Hartl-Meier, Dittmar, et al., 2014; Hartl et al., 2021, 2022; Riechelmann et al., 2020; Salzer et al., 2014; Wilson et al., 2004, 2015; Zhang et al., 2015). At lower elevations, other biotic factors, for example, intra- and interspecific competition or trophic interactions with insects, can influence tree growth (Coomes & Allen, 2007; Harr et al., 2021; Hartl-Meier et al., 2017; Hartl-Meier, Zang, et al., 2014; Saulnier et al., 2017; Wilson et al., 2015). Climate signals in tree-rings of European larch (*Larix decidua* Mill.), for example, are superimposed by growth disturbances resulting from larch budmoth (*Zeiraphera griseana* Hübner, LBM) mass outbreaks in the Alps (Baltensweiler et al., 2008; Baltensweiler & Rubli, 1999; Esper et al., 2007; Hartl et al., 2022; Hartl-Meier et al., 2017). LBM larvae feed on the needles of larch trees, lowering photosynthetic capacity and altering growth rates (Baltensweiler & Rubli, 1984). Various studies on LBM mass outbreak cyclicity and effects on larch growth conducted in the European Alps agree on an occurrence rate of mass outbreaks of 8–10 years and constrain outbreak locations largely to elevations between 1700 and 2000 m asl (Baltensweiler et al., 2008; Baltensweiler & Rubli, 1999; Büntgen et al., 2009; Daux et al., 2011; Esper et al., 2007; Hartl et al., 2022; Hartl-Meier et al., 2016, 2017; Konter et al., 2015; Rolland et al., 2001; Saulnier et al., 2017). Consequently, elevational classification of larch wood from such regions will be determined by the potentially inherent LBM signals of historical series.

For paleoclimatological studies, the knowledge of the sample origin of historical material is likewise important to adequately remove age-dependent growth trends (Bräker, 1981). The commonly applied regional curve standardization (RCS; Briffa et al., 1992) must be performed site by site or on mean-adjusted series (Römer et al., 2021; Zhang et al., 2015), because altitude-dependent offsets among MXD (and TRW) series are observed for European larch (Hartl et al., 2022; King et al., 2013; Riechelmann et al., 2020; Rozenberg et al., 2020; Zhang et al., 2015). Neglecting the elevational discrepancies of the regional curves could bias the amplitudes and long-term trends of a subsequent climate reconstruction severely, thus leading to a misinterpretation of past climate variability (Hartl et al., 2022; Riechelmann et al., 2020; Zhang et al., 2015).

In this study, we aim at improving dendroprovenancing by applying state-of-the-art ML procedures to eventually strengthen millennium-length climate reconstructions. We use 149 samples of living larch trees from an elevational transect ranging from 1400 to 2200 m asl in the Simplon Valley of the Swiss Alps and test nine different ML algorithms. We fit the best performing algorithm to different sets of tree-ring parameters and, for the first time, include x-ray measurements and species-specific parameters in a provenance model.

MATERIALS AND METHODS

Tree-ring datasets and study area

Eight larch datasets were collected in the Simplon Valley, Switzerland. One of these contains 99 historical series from different buildings in the Simplon Village (~1470 m asl) (introduced in Riechelmann et al., 2013, 2020). The seven living tree sites span an elevational transect from 1400 to 2200 m asl, with four sites south exposed (S14, S17, S20, and S22) and three north exposed (N16, N17, and N19) (Figure 1; Appendix S1: Table S1). Each site consists of up to 24 series from 12 trees (see Hartl et al., 2022). The two sites at 1700 m asl (S17 and N17) are merged to one dataset SN17 including 12 series from each site to represent this elevation. Both, the living and historical series, have been accurately dated to build a robust chronology (Figure 2).

Dendrochronological measurements and tree-ring parameters

In total, 242 high-resolution tree-ring density profiles were measured using a Walesch2003 (WALESCH, Electronic GmbH, Switzerland) following the x-ray densitometry procedure described in Björklund et al. (2019). We considered six different tree-ring parameters: TRW, MXD, earlywood ring width (EWW), earlywood density (EWD), latewood ring width (LWW), and latewood density (LWD) (Appendix S1: Table S2). Descriptive statistics were calculated and forwarded into the ML models including the arithmetic mean, standard deviation (SD), skewness (skew), Gini coefficient (gini), and maximum/minimum values (max/min). Additional parameters include the age (including the pith offset), the first-order autocorrelation of TRW (A1 TRW), and the ratio between EWD and LWD (ED/LD ratio). To address the LBM mass outbreak mean cyclicity of 9 years, the spectrum value at 1.11 frequency (9 years) was determined by applying Lomb–Scargle Fourier transformation to 30-year spline detrended TRW series. A dataset D of all living series containing their parameters, from here on referred to as features, and corresponding elevations was created using R 4.1.0 (R Core Team, 2021) and the dplR package (Bunn, 2010).

Site-specific chronology building and climate signals

To illustrate the fading of the temperature signal with decreasing elevation, the living tree-ring data (TRW and MXD) were site-wise power transformed and RCS detrended (Briffa et al., 1992; Esper et al., 2003) using the software ARSTAN (Cook, 1985). Site chronologies were constructed by averaging single series with a robust mean and the chronology variance was stabilized using the Rbar weighted method (Osborn et al., 1997). Temperature correlations between site chronologies and gridded temperature data (EOBS 0.25° v23.1e; Cornes et al., 2018) were

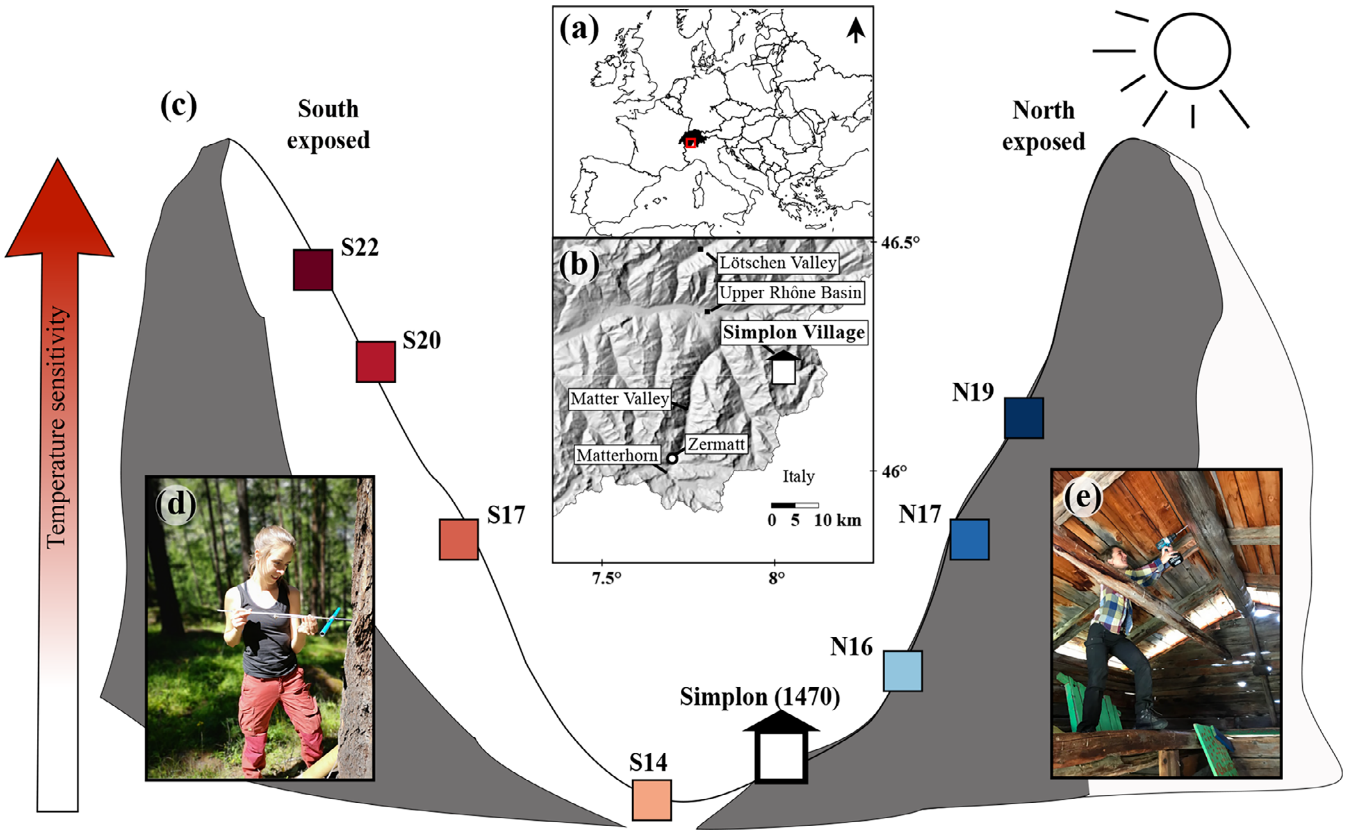

FIGURE 1 Study area in the Simplon Valley, Switzerland (a, b) and sampling scheme with site codes (c), exact elevations are shown in Appendix S1: Table S1. Sampling of high-elevation living trees with a high temperature sensitivity (d) and of historical construction timber in the lower elevated Simplon Village (e) (Photo credits: P. Schulz, C. Hartl).

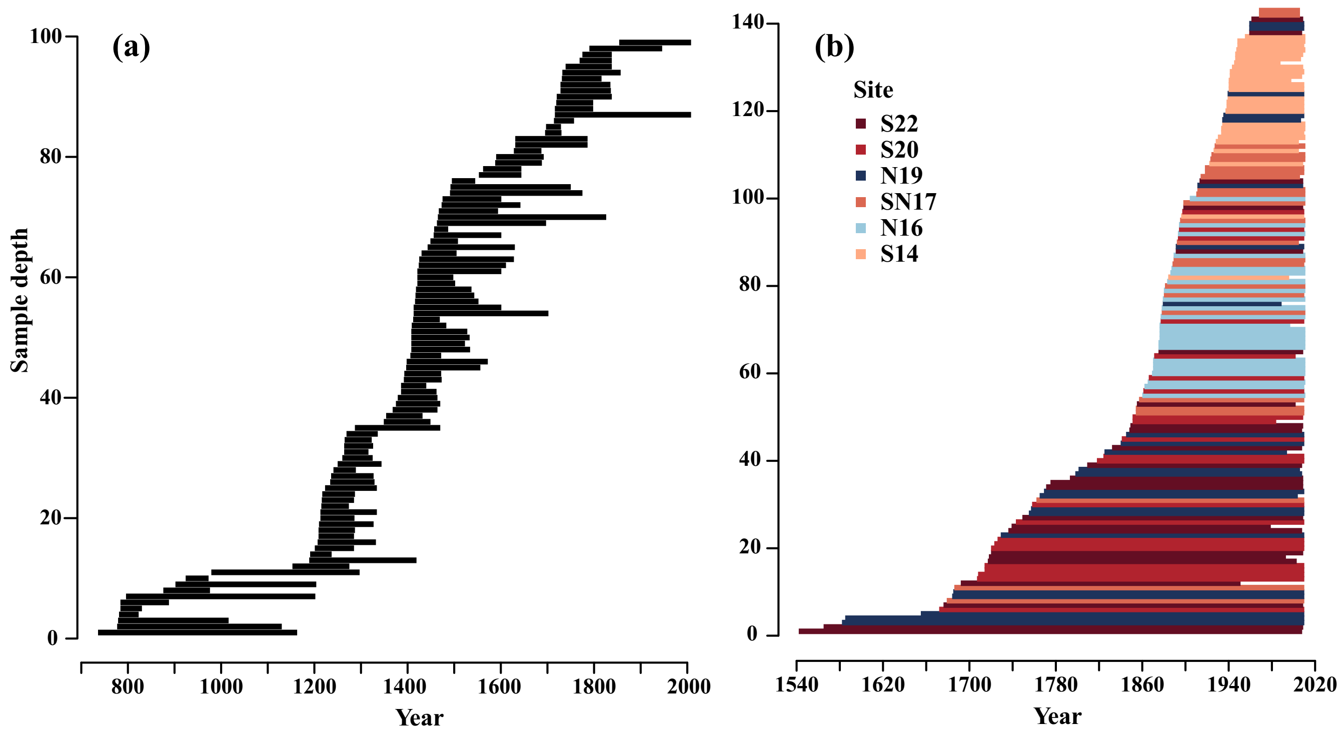

FIGURE 2 Segment plots of the historic (a) and the living tree samples (b) aligned by start date. Colors in (b) denote the different sites of the living material (Figure 1c).

calculated via classical bootstrap of Pearson's correlation coefficients for the summer seasons June–August (JJA) over the 1928–2009 common period using the R packages treeclim (Zang & Biondi, 2015) and dplR (Bunn, 2010).

Developing a ML model for dendroprovenancing

In supervised learning, a model is fit for a classification or regression task to a labeled dataset (e.g., D) (Figure 3a). Using a training dataset D_{train} of an input matrix X, the model must predict the corresponding target vector y with a prediction $\hat{y}$. During training, the settings of the given model are adjusted by computing and minimizing the total loss

$$L = \sum_{i=1}^{m} l(y_i, \hat{y}_i), \tag{1}$$

where m equals the number of entries (number of tree-ring series) in D_{train} and l is a loss function (e.g., cross-entropy). To assure that the model has not only learned D_{train} by heart but has adopted a meaningful representation that generalizes to unseen data, it is applied to a test dataset D_{test}. Potential hyperparameters of a model can be adjusted using a validation dataset D_{val} (Vapnik, 1991; Ying, 2019). Here, the input matrix X of the 143 living tree series from varying elevational sites between 1400 and 2200 m asl was split into D_{train} and D_{test} using a stratified sampling by elevation to ensure a representation of all sites in both sets (80:20 split). In the second split, D_{train} was divided by stratified sampling into the final D_{train} and D_{val} (80:20 split). We tested nine different ML classification algorithms on D_{train}: kNN (Fix & Hodges, 1951), Ridge Regression (Hoerl & Kennard, 2000), Logistic Regression (here Softmax Regression) (Berkson, 1944), Support Vector Machines (Vapnik & Chervonenkis, 1974), Stochastic Gradient Decent (Kiefer & Wolfowitz, 1952), Gaussian Naïve Bayes (Zhang, 2004), Random Forest (Breiman, 2001), Linear Discriminant Analysis (Fisher, 1936), and Extreme Gradient Boosting (XGBoost) (Chen & Guestrin, 2016). The hyperparameters of the algorithms (e.g., maximum tree depth or learning rate) were fine-tuned using grid search and stratified k-fold cross-validation ($k = 10$) on D_{train} ensuring the consideration of the specified combinations (chosen hyperparameters are listed in Appendix S1: Table S3). Afterwards, the models' performances were tested again on D_{train} using a repeated stratified k-fold cross-validation ($k = 10$ and repeats $= 100$) to choose the best performing ML algorithm.

We measured the performance of the models using f_1 score, precision, and recall:

$$f_1 \text{ score} = 2 \times \frac{\text{precision} \times \text{recall}}{\text{precision} + \text{recall}}, \tag{2}$$

with

$$\text{precision} = \frac{\text{TruePositive}}{\text{TruePositive} + \text{FalsePositive}}, \tag{3}$$

and

$$\text{recall} = \frac{\text{TruePositive}}{\text{TruePositive} + \text{FalseNegative}}. \tag{4}$$

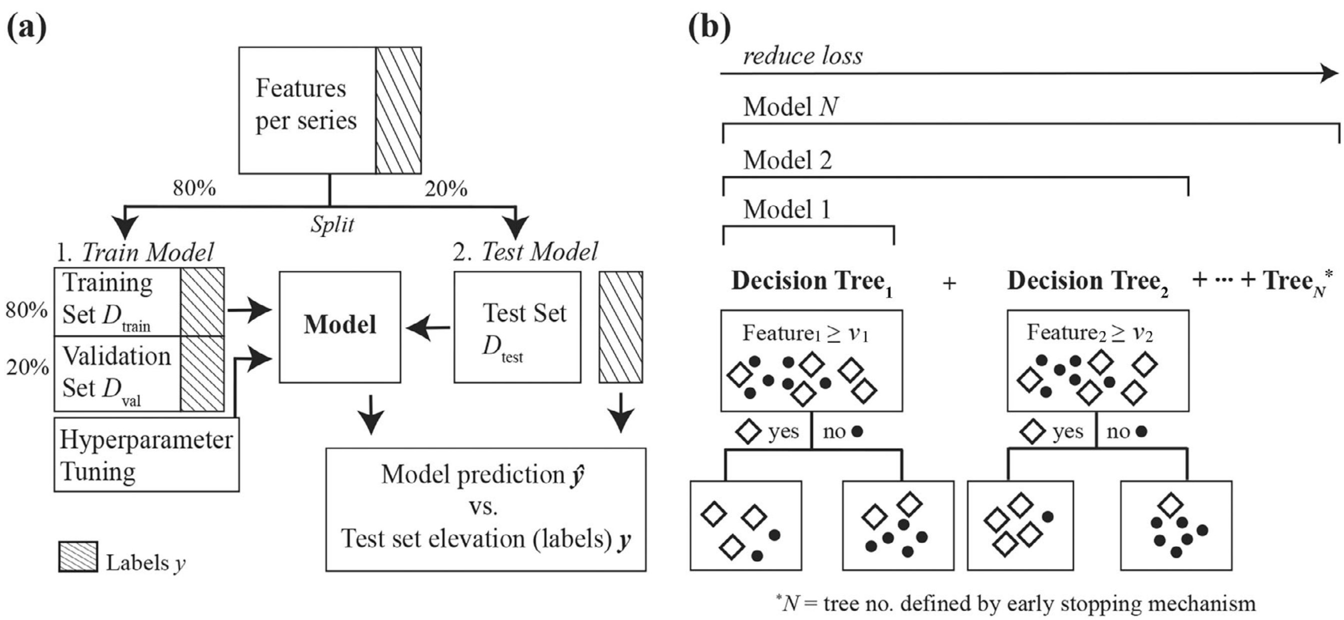

FIGURE 3 Basic machine learning scheme (a) and a simplified gradient boosting scheme (b) with two classes (solid circle or open diamond).

Precision describes the correctly sorted series per elevational class, while recall counts the number of series, which belong to a certain class but are not predicted into it (Géron, 2019). The f_1 score over all classes per model was calculated as the arithmetic mean.

We find that highest f_1 scores are reached by the XGBoost algorithm (Appendix S1: Table S4) after stratified repeated *k*-fold cross-validation with a mean f_1 score of 0.7. XGBoost (Chen & Guestrin, 2016) is based on the gradient boosting algorithm by Friedman (2001), which iteratively builds an ensemble model consisting of multiple decision trees by minimizing the loss function in each iteration (see Figure 3b as simplified classification scheme with two target classes [solid circle or open diamond]). The algorithm proceeds until a final model *N* is found specified by a stopping criterion (Ying, 2019).

Based on the applicability in tree-ring science, four different XGBoost models were trained on different combinations of the features. Two models were trained on all density and ring-width features: a general not species-related (39 features, DM_{gen}) and a larch-specific model including the 9-year spectrum (40 features, DM_{sp}). Two additional models excluding densitometric measured features were built: a general cross-species ring-width model (RWM_{gen}, seven features) and a larch-specific ring-width model (RWM_{sp}, eight features). The average and site-wise performances of these models were assessed on D_{test}. Finally, a feature matrix for the historical timber was built and fed to the four XGBoost models. All models were implemented in Python 3.8.5 (Van Rossum & Drake, 2009) with the packages Scikit-Learn (Pedregosa et al., 2011) and XGBoost (Chen & Guestrin, 2016).

For comparison with existing methods for dendroprovenancing, we additionally tested the performance of these approaches with our living series of D_{train} and D_{test}. We built a regression model from the D_{train} tree-ring series (following the approach of Wilson et al., 2004) based on the correlation between the individual site chronologies and the highest elevation chronology S22 (2200 m asl). We also tested a PCGA approach (Buras et al., 2016) on our tree-ring parameters (TRW, MXD, EWW, EWD, LWW, and LWD) to check for differences in PCGA loadings. The tree-ring series of D_{test} were then sorted to a provenance following the steps described in Akhmetzyanov et al. (2019, 2020). We used our LWD densitometry measurements as equivalent substitutes for their use of latewood blue intensity (Campbell et al., 2007). Precision, recall, and f_1 score were calculated for these approaches to compare them with our XGBoost models (Equations 2–4).

RESULTS AND DISCUSSION

Model performances on the test dataset

Testing the models revealed that DM_{sp} and RWM_{sp} (Table 1) perform better than their species-independent equivalents DM_{gen} and RWM_{gen} (Appendix S1: Table S5). While DM_{gen} and RWM_{gen} reach average f_1 scores of 0.69 and 0.25, the inclusion of the larch-specific LBM feature increases the scores to 0.80 (DM_{sp}) and 0.31 (RWM_{sp}), respectively. In DM_{sp}, the highest site-wise f_1 scores are observed for the sites S22, N16, and S20 and it executes better than DM_{gen} in almost all sites, except for the highest and the lowest elevations. This performance gain is most pronounced in SN17 and N19. The provenance model results (Figure 4) imply that the LBM signals appear to be stronger at these sites and serve as an important feature for site distinctions in DM_{sp} (Figure 4c). This is also reflected by the high feature importance of the LBM spectrum (Figure 4d) and the increased performance of RWM_{sp} compared with RWM_{gen} at site N19 (Table 1, Appendix S1: Table S5). Our results indicate that future applications of likewise models should be tested with and without tree species-related characteristics (e.g., interactions with insects) when specific influences on growth are known and observed. Even though the ring-width models themselves are not very reliable, including site- or species-specific information improved the model's ability to distinguish sites (mean f_1 scores: 0.25 in RWM_{gen} and 0.31 in RWM_{sp}). The comparison of models with and without disturbance effects can offer the chance to detect site-specific influences such as LBM mass outbreaks and support the assessment of past disturbances in historical series. However, the increased performances of the larch-specific models in our example reflect the distinct impact of LBM outbreaks on larch

TABLE 1 Classification report: performance metrics of D_{test}[a] on DM_{sp}[b] and RWM_{sp}[c] (in brackets) in each individual class.

Site	Precision	Recall	f_1 score
S14	0.57 (0.57)	0.8 (0.8)	0.67 (0.67)
N16	1 (0.40)	1 (0.4)	1 (0.4)
SN17	0.75 (0.0)	0.6 (0.0)	0.67 (0.0)
N19	0.6 (0.6)	0.6 (0.6)	0.6 (0.6)
S20	1 (0.0)	0.75 (0.0)	0.86 (0.0)
S22	1 (0.17)	1 (0.2)	1 (0.18)
Average	0.82 (0.29)	0.79 (0.33)	0.8 (0.31)

[a]Test dataset.
[b]Larch specified density and ring-width parameter model.
[c]Larch specified ring-width parameter model.

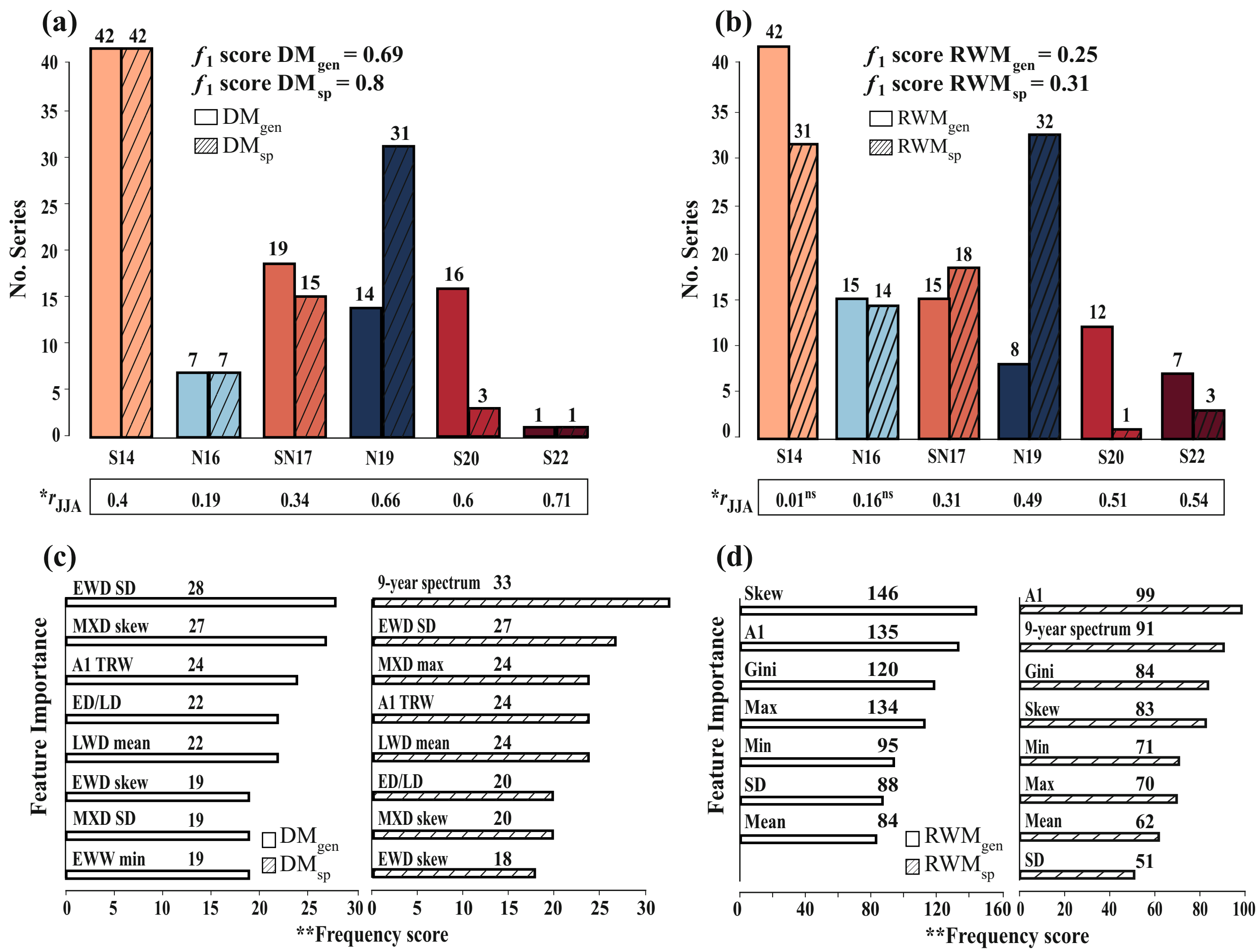

FIGURE 4 Classified historic timber by DM_{sp} (larch specified density and ring-width parameter model) and DM_{gen} (general unspecified density and ring-width parameter model) (a). Accordingly, RWM_{sp} (larch specified ring-width parameter model) and RWM_{gen} (general unspecified ring-width parameter model) (b), including the f_1 score of D_{test} (test dataset) and correlations between EOBS 0.25° mean temperature data for June–August ($*r_{JJA}$) and MXD (maximum latewood density) (a) and TRW (tree-ring width) (b) chronologies, respectively. Correlations tagged with ns have no significant correlation. (c) and (d) illustrate the most important features of the models above. **Frequency score refers to the no. decision tree nodes a feature was used for (see methods for detailed information on feature abbreviations).

growth and raise the question of whether general not species-related models will have increased performances when applied to undisturbed nonhost species like the Swiss pine (*Pinus cembra* L.). In the Simplon Valley, the inherent LBM signal strength on certain elevations has a strong influence on the performance of provenance models for larch trees. When working with species, which react similarly to a disturbance, a feature that describes the strength of this disturbance on each individual tree-ring series should be considered.

Including tree-ring density features generally improves model results. The ring-width models are not able to distinguish SN17 and S20 from the other sites (f_1 scores = 0; Table 1; Appendix S1: Table S5), produce more classification errors on D_{test} than the density models (sum of errors for $RWM_{gen} = 21$, $RWM_{sp} = 19$, $DM_{gen} = 9$ and $DM_{sp} = 6$), and misclassify series belonging to SN17 to S22. With respect to detrending, mistakenly handling low-elevation series as high-elevation series can impact a mean chronology, particularly when such misplaced series are clustered during certain periods. Additionally, RWM_{gen} sorts series from N19, characterized by higher temperature sensitivities, to the lowest elevated site, which contains no temperature signal (see r_{JJA} in Figure 4b). These errors will, however, not influence a temperature reconstruction, as sites with a low climate response should be excluded from a final chronology. Nonetheless, the sample replication of useful historical series would be reduced and uncertainties increased. In the Simplon Valley, the ring-width models appear to lack the ability to correctly determine the provenance and distinguish minor elevational differences (≤200 m), although small-scale elevation steps can result in differences in a tree species growth response to environmental factors (r_{JJA} in Figure 4a,b; Bunn et al., 2011; Hartl et al., 2022; Salzer et al., 2009, 2014).

The applied XGBoost algorithm is not able to find a well-fitting model when trained on our ring-width features and, as Akhmetzyanov et al. (2019) have already shown for dendroprovenancing with PCGA, performs better when tree-ring density measurements are included. We suggest using DM_{sp} for finding the provenance of our historical tree-ring series, as it is the most reliable model indicated by the highest f_1 score and lowest number of prediction errors. This unique dataset including density measurements and LBM features is, however, tailored to larch trees from the Simplon Valley. Datasets of varying species and other regions might perform better with a different algorithm.

Extreme gradient boosting models compared with previous dendroprovenancing approaches

The performance of previous approaches on D_{test} indicates that these approaches are not suitable for our data as they show lower performance scores and higher error numbers than our DM_{sp}. The application of PCGA to find the provenance of the D_{test} series resulted in f_1 scores of 0.28 (LWD) and 0.16 (TRW), respectively (Appendix S1: Figure S1a–c). PCGA has demonstrated the ability to distinguish between high- and low-elevation sites (Akhmetzyanov et al., 2020) but does not appear to be able to determine the provenance of the series as precise as the XGBoost model in this study. Utilizing the method described in Wilson et al. (2004) on the dataset indicates a nonlinear correlation between the highest site and the other elevational chronologies (Appendix S1: Figure S1a,d). The striking low correlation between the highest site and the N19 chronology might result from differing LBM signals between the sites, which is supported by the observed performance decrease in DM_{gen} compared with DM_{sp} at N19 (Table 1; Appendix S1: Table S5). Thus, fitting a linear regression model on the series of D_{train} and testing this model using D_{test} reveals a lower f_1 score of 0.25 (Appendix S1: Figure S1a).

Most existing approaches depend on a common period between the historical and living tree-ring series, but even when a common period is given, DM_{sp}, DM_{gen}, and RWM_{sp} outperform traditional dendroprovenancing approaches on our dataset. The XGBoost models (but also all other tested ML models, Appendix S1: Tables S3 and S4) do not require a common period. Our approach has the advantage of including specifications on certain regions or tree species (here European larch) if needed and could likewise be applied to other dendroprovenancing objectives, such as shipwrecks or art provenance as well as trade or transportation route studies (Bridge, 2011; Daly & Tyers, 2022; Linderholm et al., 2021; Shindo & Claude, 2019; Wazny, 2002). Testing different ML algorithms, which are independent of a common period, might enlarge the pool of useable sites for these wood provenance studies and could thereby improve detecting the geographical origin.

Dendroprovenancing of historical timber using extreme gradient boosting

The classification of historical material reveals differences between our four models (Figure 4a,b). DM_{sp}, DM_{gen}, and RWM_{gen} classify most series to the lowest site S14, while RWM_{gen} sorts most series to N19. In contrast to their general not species-related equivalents, the larch-specific models classify more series to the LBM-influenced site N19 but less series to the highest elevation sites. A comparison of the individual series predictions reveals that most of the series assigned to a higher elevation by DM_{gen} were sorted to N19 by the larch-specific DM_{sp}. This might again indicate that information on the intensity of the LBM mass outbreaks cyclicity influences a model's differentiability of these sites and thus the model outcomes. An assessment of the predictions reveals that 26% of the historical series are sorted to different sites by DM_{sp} and DM_{gen}. With respect to the better performance and lower number of errors of DM_{sp} compared with DM_{gen} during the model validations, DM_{sp} likely performs more confidently with the historic series as well. RWM_{gen} indicates a similar problem outlining a tendency to sort historical series to S20, while the larch-specific RWM_{sp} attributes them to N19. Both ring-width models have very low performance scores as well as high error numbers on D_{test} and, compared with the density models, classify 49% (RWM_{gen} to DM_{gen}) and 41% (RWM_{sp} to DM_{sp}) of the historical series differently. The discrepancy between RWM_{sp} and DM_{sp} classifications persists throughout time (Figure 5), culminating between 1250 and 1600 CE. This peak period is not covered by living material (of known origin) and erroneous predictions (e.g., from RWM_{sp}) could lead to incorrect variability or mean levels in an RCS detrended chronology when historical series sorted to wrong elevations. As varying allocations of historical series may bias long composite chronologies differently in certain time periods, these chronologies depend on a reliable provenance of historical series.

As the analyses on D_{test} imply more accurate predictions by the DM_{sp} in contrast to the other models, especially to the ring-width models, the results of the classification of historical timber by DM_{sp} should be considered for further proceedings. For a reconstruction, we suggest using series allocated to the temperature-sensitive high-elevation sites N19, S20, and S22. This will result in using only

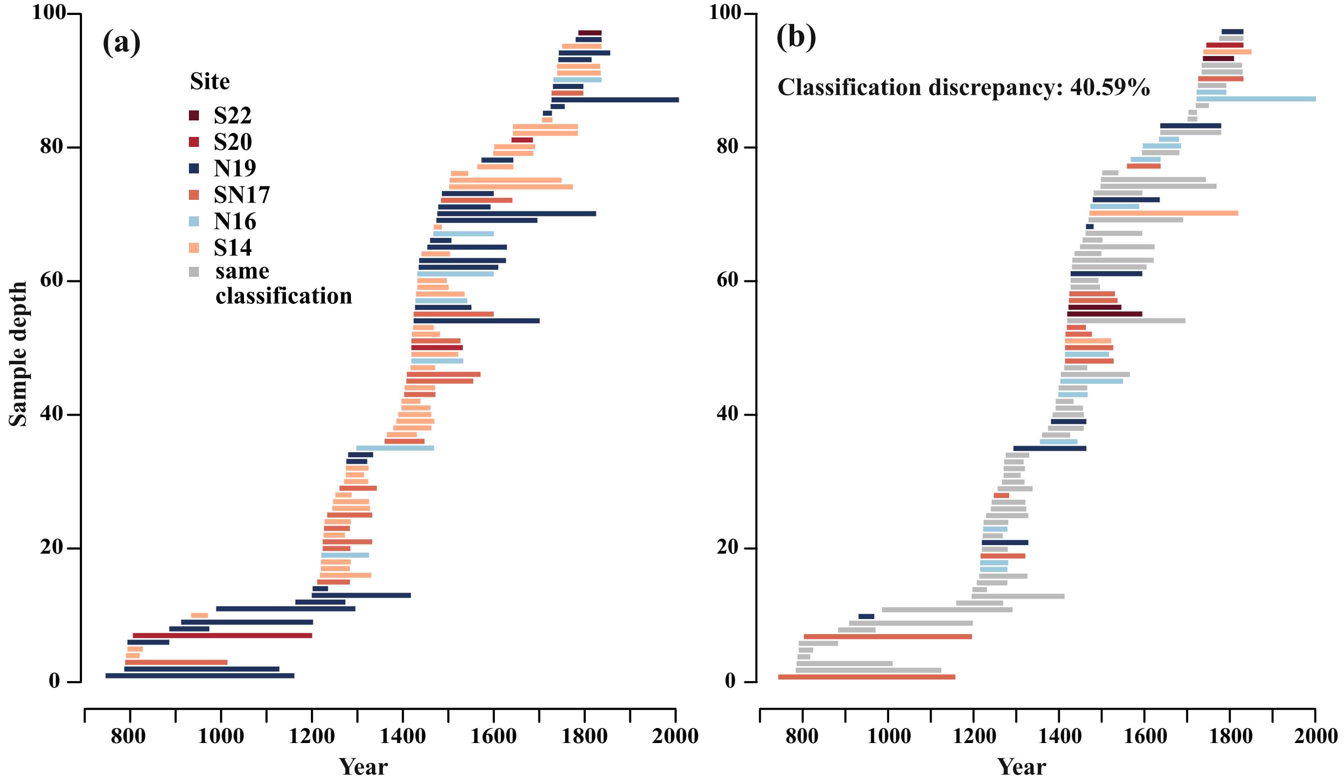

FIGURE 5 Segment plots for the classified historic timber by DM_{sp} (larch specified density and ring-width parameter model) (a) and RWM_{sp} (larch specified ring-width parameter model) (b). Colors in (a) denote the different elevational classes, the historical material was grouped by DM_{sp}. In comparison to (a), identical classifications of DM_{sp} and RWM_{sp} are grayed in (b). Colors in (b) pronounce classification differences and give the respective class.

35 of 99 historical series but will improve the robustness of the signal strength of these series. In the Simplon Valley, these high-elevated sites show distinct offsets in their regional curves (Hartl et al., 2022), which must be considered when merging samples and sites into one RCS run (Esper et al., 2014). Excluding 54 historical series from a chronology would, however, massively reduce the sample replication. The period between 742 and 1450 CE will almost never exceed five series per year and puts the development of a continuous millennium-length climate reconstruction at risk. Tree line shifts during the last millennium can alter the elevational temperature signal strength and bias climate reconstructions (Büntgen et al., 2022). The provenance model cannot account for temporal changes in tree line elevation, but it helps reduce the bias by excluding historical series classified to recent lower elevations and reveals the series from close tree line sites with a very high likeliness of high temperature sensitivity.

Outlook and future applications of ML algorithms in dendroprovenancing

Our new approach for dendroprovenancing using ML shows considerable skill to differentiate tree-ring samples over short distances and among different elevations. While this application is limited to the Simplon Valley in the Swiss Alps and European larch, the proposed scheme (Figure 3a) could similarly be applied in other provenance studies. If suitable, existing multi-centennial to -millennial long chronologies, based on ex situ historical or relict wood, might be improved using ML techniques. Improved provenance determination of dead wood will increase the temporal stability of the climate signal of a chronology and enable a more reliable reconstruction of past climate.

Algorithms may also be trained with geographical coordinates as target *y* and a matrix *X* of series features from different chronologies to detect wood trade routes and origins of art or ship timber. It is mentionable that for different study areas, the chosen final algorithm might not match our best performing one, since tested algorithms might outperform each other differently depending on the region or species (Wolpert, 1996). We acknowledge that the available features in this study are unique and are often not available in this quantity, hindering the exact reproduction of the models. We consider the selected basic features of our study as a good starting point, which can be extended with other tree-ring parameters, for example, blue intensity, wood anatomical features, dendrochemical parameters, biomarkers, or isotopic signatures, that are already tested in other provenance studies (e.g., Akhmetzyanov et al., 2020; Domínguez-Delmás et al., 2020; Hajj et al., 2017; Traoré et al., 2018). In the presented study, the LMB influence strongly impacts the performance of our models. Therefore, we suggest testing our approach with a nonhost species, that is, with the tree-ring series of previous approaches, to compare general cross-species models with each other. We hypothesize that the reduced performance of a general cross-species model (DM_{sp} and RWM_{sp}) likely results from the LBM manifestations in the larch samples. Using an undisturbed tree species might also result in better performances of the ring-width models. More data from living trees would likely improve training in the presented models. The DM_{sp} should especially be tested in future studies using corresponding blue intensity features, because it is a less labor- and cost-intensive approach for gaining information on tree-ring density (Björklund et al., 2014; Campbell et al., 2007; McCarroll et al., 2002).

CONCLUSION

Our novel approach using the ML algorithm XGBoost with tree-ring density and width data including species-specific features (DM_{sp}) improved to determine the provenance of wood of unknown origin without relying on a common period with (living tree) reference data. The origin of 99 historical series was assigned along an elevational transect ranging from 1400 to 2200 m asl. Importantly, series from sites with diverging temperature responses have been identified and were consequentially excluded from a reconstruction. Our approach enables the user to include multiple parameters of individual trees and species and test various ML algorithms. It reveals how model performances are impacted by tree growth disturbances and how these performances can be used to detect the strength of growth disturbances. Our novel approach may serve as a framework for future applications of ML and dendroprovenancing in tree-ring research.

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CONFLICT OF INTEREST STATEMENT

The authors declare that they have no conflict of interest.

DATA AVAILABILITY STATEMENT

Data (Kuhl et al., 2023) are available from Figshare: https://doi.org/10.6084/m9.figshare.c.6412304.v1.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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