



Using random forests and dendroclimatology to reveal climatic factors in tree growth – case studies from temperate and tropical regions

Finn Moormann¹ · Michael Köhl¹

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Abstract

In this study, we analyse the suitability of the machine learning algorithm Random Forest in exploring dendroclimatic relationships. Linear methods are commonly used to explain climate related changes in radial growth, but inherently fail to capture thresholds and nonlinear effects contained in the data. Machine learning applications like Random Forest can potentially fill this gap. We use tree ring chronologies from three temperate coniferous tree species *Picea abies*, *Pseudotsuga menziesii* and *Pinus sylvestris* from northern Germany as well as a chronology from *Cedrela odorata* grown in a tropical forest in Suriname to compare response function correlation and Random Forest variable importance for monthly temperature and precipitation values on tree ring width. We further explore the possibilities of using Accumulated Local Effects to display nonlinear effects on tree ring increment. Our results show that Random Forest importance aligns well with response function analysis for the temperate species and mostly aligns with the results on *Cedrela odorata*. Accumulated Local Effect plots offer valuable insights into nonlinear climate effects and help in explaining unexpected correlations. While the Random Forest algorithm is not a complete substitute for established methods like response function analysis to analyse climate-growth relations, it is a valuable addition to the available toolset in exploring the hidden information in dendrochronological data.

Key message

The Random Forest algorithm can provide valuable insights about dendroclimatic relationships, Complementing established methods like response function analysis by identifying nonlinear effects and thresholds

Keywords Machine learning · Random forest · Climate signals · Dendrochronology · Tree rings · Artificial intelligence

Abbreviations

ANN	Artificial neural networks
ALE	Accumulated local effects
IncMSE	Increase in mean squared error
OOB	Out-of-bag
PD	Partial dependence
RF	Random forest

RFA	Response function analysis
TSCV	Time series cross-validation

Introduction

Annual tree rings hold unique information on growth conditions that can be dated back thousands of years through overlapping chronologies (Schweingruber 2007). This information has been used in dendrochronology for various applications like the dating of historical samples (Bauch and Eckstein 1981; Rubino and Baas 2019) or the reconstruction of past climates (Briffa 1990; Cook et al. 2002; Nicault et al. 2008; Björklund et al. 2023). The later application, also known as the subfield of dendroclimatology, originally focuses on obtaining climate information from the growth ring characteristics. Vice versa, tree ring records can be used

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✉ Finn Moormann
finn.moormann@uni-hamburg.de
Michael Köhl
michael.koehl@uni-hamburg.de

¹ University of Hamburg, Institute of Wood Science – World Forestry, Ohnhorststraße 18, 22609 Hamburg, Germany

to obtain information about the influence of climatic conditions on the growth of trees (e.g. Luckman 2013; Vejputsková and Čihák 2019; Gauli et al. 2022), which can help in understanding the impact of the accelerating anthropogenic climate change. By now, the methods used for this are well established, with linear models like linear regression, stepwise multiple regression, and multivariate response function being predominantly used (Fritts 1976). Recent implementations of correlation and response functions include Biondi and Waikul (2004) and Meko et al. (2011).

It is known, however, that physiological processes often have nonlinear responses to climatic factors, like the relationship between net-photosynthesis and daily temperature (Hikosaka et al. 2006). Cook and Pederson (2011) discuss the role of nonlinear models in climate reconstructions. They state that, even though physiological processes and rates of reaction leading to growth ring formation are knowingly nonlinear, the aggregate of these interacting processes often leads to an effectively linear signal in the growth rings, which explains the good results obtained in a wide range of dendrochronological studies. But with global warming, climatic conditions will more frequently exceed the trees' adaptive range. Linear estimates might not sufficiently capture the growth reactions in the extreme cases. Consequently, Wilmking et al. (2020) calls for using nonlinear analysis of growth ring records. Meko and Baisan (2001) and Meko et al. (2020) accounted for nonlinearity in tree ring responses to summer drought and river floods respectively by using a classification tree model. A different approach in modelling these relationships is the use of machine learning, a field that finds increasing attention in forestry related research (Liu et al. 2018). In dendroclimatology, Artificial Neural Networks (ANNs) have been used by multiple authors to better model the nonlinear climate-growth relationships. While Woodhouse (1999) identified the problem that ANNs have the tendency to overfit the data compared to the linear model, later studies constructed ANN models that outperform the linear approaches (D'Odorico et al. 2000; Zhang et al. 2000). Jevšenak and Levanič (2016) compared linear models and ANN models on three sites and produced a better fit with ANN in all cases. They state that, as a properly selected training algorithm prevents overfitting, ANNs are generally a more effective method. Decision tree based machine learning algorithms like Random Forest (RF) have received comparably little attention in dendroclimatology, despite offering several advantages. Decision trees are easier to interpret, and can handle a wide range of input data, including differently scaled numerical data as well as categorical data. Touw et al. (2013) empathize the suitability of RF in life sciences in general. They ascribe this to two aspects—its high prediction accuracy and information on variable importance. Additionally, RF performs very

well in cases where a small number of observations meets a wide range of variables (Strobl et al. 2007; Touw et al. 2013), as it is often the case in biological data. Weiskittel et al. (2011) used RF to predict Site Index and Gross Primary Production from climate data, and Jevšenak et al. (2018) used RF to model basal area increment for data of the Slovenian National Forest Inventory. Additionally, they simulated input variables over their range while keeping the other values at their mean, obtaining variable effects and showing that RF can help the interpretation of impact variables. Only recently, dendrochronological studies have incorporated RF models into their research (Tallieu et al. 2020; Kuhl et al. 2023; Pavão et al. 2024).

With this study, we aim to evaluate the effectiveness of RF in detecting climate-growth relationships in tree rings by comparing the results of the RF model to the widely used response function analysis (RFA). While many machine learning applications try to model data with the goal of prediction, our focus is on the interpretation of the data. We use tree ring chronologies of *Picea abies* L. (Norway spruce), *Pseudotsuga menziesii* (Douglas fir) and *Pinus sylvestris* L. (Scots pine) from Scharbeutz, Germany, following Gauli et al. (2022). Additionally, a chronology of *Cedrela odorata* L. (Cedro hembra or Spanish cedar) is analysed utilizing the same methods to study the approach in tropical conditions. Furthermore, we show the potential of RF models to depict nonlinear climate-growth relationships to demonstrate their potential for future dendrochronological research.

Materials and methods

Tree selection

For this study four tree species were selected. Three of the selected species, *Picea abies* L. (Norway spruce), *Pinus sylvestris* L. (Scots pine), and *Pseudotsuga menziesii* (Douglas fir) are coniferous trees native in temperate climate. They are important species for commercial uses and commonly used in dendrochronology. The cores were collected in a stand located in Scharbeutz, in the federal state of Schleswig-Holstein, Germany. The stand is an even-aged forest, planted in the late nineteenth century, with the dominant species being *Abies grandis* (Giant fir), *Fagus sylvatica* (Common beech) and the previously mentioned species. The area consists of a predominantly moderately fresh low-loamy soil with a moderate nutrient supply and spans over an altitude of 6 m to 43 m. These three species from the same stand were selected to have illustrative samples for the case studies. The fourth species, *Cedrela odorata* L. (Cedro hembra or Spanish cedar), is a deciduous tree of the Meliaceae family. It is native in moist American tropical forests and, although

not being abundant in its habitats, an important commercial species. Due to its distinctive growth rings it is well suited for tree ring analysis (Lotfiomran and Köhl 2017). We included this species to extend the range of these case studies with a broadleaf species and different climate conditions. Annual growth ring formation for Cedro is likely linked to the dry season with precipitation below 100 mm per month that takes place from September to November in the Suriname region, with ring formation happening at the beginning of the dry season (Worbes 1995).

Tree ring samples

For each species in the Scharbeutz data, two cores from 20 randomly selected dominant trees were taken at breast height (1.3 m) using a 5 mm increment borer. For Cedro, stem discs were taken from 20 randomly selected trees felled for commercial timber use. All trees were harvested in the central part of the natural rainforest belt of Suriname. Both the cores and the stem discs were then dried and sanded for further measurements. For this, a LINTAB (linear positioning table), connected to a PC with TSAP-win (time series analysis package for windows) was used. Measurement data was further checked for apparent measurement errors by cross-examining the samples from the same tree and remeasured if necessary.

Chronology building

Chronology building was done using the R package *dplR* (Bunn 2008) following the method used by Gaudi et al. (2022). A double detrending method was applied to each tree ring series, with modified negative exponential curves followed by a smoothing cubic spline with a 50% wavelength cutoff to 67% of the series length. This procedure aims to remove any long-term growth effects overlaying climatic effects, while maintaining short-term growth changes. The chronology for each of the four species was created by forming the arithmetic mean over the respective detrended tree ring series indices. Lastly, the autocorrelation for every individual series was removed using autoregressive models with a maximum order of three (Fig 1). The Expressed Population Signal (EPS) of the chronologies in the considered periods is at 0.87 for spruce, 0.83 for Douglas, 0.84 for pine and 0.88 for Cedro.

Climate data

The Scharbeutz climate data were obtained from the German Meteorological Service (DWD). The DWD provides monthly climate data in a 1 km × 1 km spatial resolution. For each tree, the closest responding climate data point was

assigned. The aggregated mean value of the trees' climate data was then used as climate data for the stand chronology. The meteorological data in Suriname were measured at the meteorological station in Zanderij, which is around 50 km from the stand origin, and were provided by the Meteorological Service Suriname (MDS). For testing the ability of the RF model to portray climate-growth relationships, monthly mean temperature and total monthly precipitation were used. The timescale for the Scharbeutz data extended from June of the previous year relative to growth ring formation to October of the current year. Each considered month was thereby handled as an input variable, resulting in a total of 34 input variables. Temperature and precipitation values for Scharbeutz start from year 1900 until 2020. For Cedro, the full year of ring formation and all months of the previous year are used, resulting in 48 input variables. As precipitation measurements did not start before 1960, only data from this point onwards until 2012 were used for the analysis (Fig 2). Annual mean values for the respective time periods are displayed in Fig 3. Mean monthly values can be found in the supplementary material.

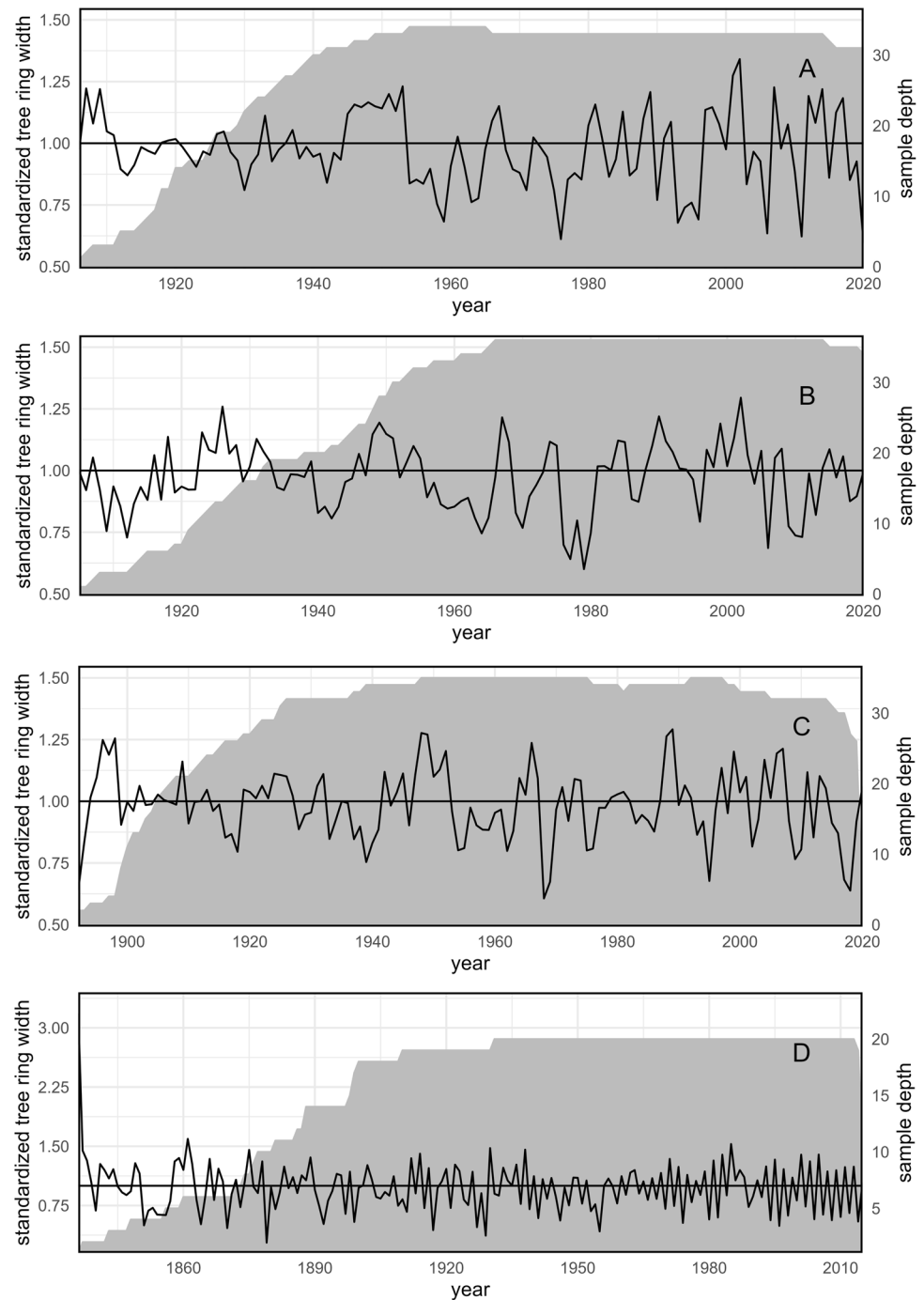
Response function

For the comparison of results from the RF model, a bootstrapped response function, implemented in the R package *treeclim* (Zang and Biondi 2015), based on the C++ package *DENDROCLIM2002* (Biondi and Waikul 2004) and its R implementation *bootRes* (Zang and Biondi 2013), respectively, was used. The response function works by creating a matrix of the standardized predictor variables (monthly mean temperature and monthly precipitation in this analysis). From this, a covariance matrix is computed that summarizes the relationships between all pairs of variables. A principal component analysis (PCA) is then used to compute eigenvectors and eigenvalues of this matrix. Eigenvectors are ranked by their corresponding eigenvalues and then selected using the PVP criterion (Guiot 1990), retaining only the important eigenvalues. The estimators of the response function are then obtained by application of ordinary least squares. Mathematical details can be found in (Zang and Biondi 2013). Median coefficients are categorized as significant at the $P=0.05$ level when their absolute values exceed half the difference between the 97.5th quantile and the 2.5th quantile of the 1000 bootstrapped samples (Biondi and Waikul 2004).

Random forest

The RF algorithm is a decision-tree based, supervised machine learning algorithm. It produces a multitude of decision-tree predictors of which the majority vote or the

Fig. 1 Ring width chronologies of spruce (A), Douglas (B), pine (C) and Cedro (D). The plotted line indicates the ring width index (left y-axes). The grey area indicates number of core samples (A, B, C) or disk samples (D) from the period.



average yields the result for classification or regression tasks, respectively. The algorithm's accuracy increases with the strength of the individual decision tree predictors and decreases with the predictor tree correlation. To decrease predictor tree correlation, RF uses a combination of bagging and random feature selection.

In bagging (bootstrap aggregating), for each predictor, a subset of the training data gets created by random drawing with replacement. However, with this randomization process alone, all decision trees will still have a similar structure,

with the most influential variables being selected for the top nodes at every decision tree. To reduce this correlation between the decision trees, for each node, a random subset of input variables – referred to as features—is selected for the split. Usually, the number of features $m = p/3$ for regression and $m = \sqrt{p}$ for classification are being used, with p being the total number of test set variables. A large number of features increases the strength of each predictor tree, but also the correlation between the predictor trees. Thus, a medium number provides the best results (Breiman 2001).

Fig. 2 Walter-Lieth climate diagram for the metrological stations in Zanderij, Suriname (left) and Scharbeutz, Germany (right). The left y-axes show temperature ($^{\circ}\text{C}$), the right y-axes show precipitation (mm). Months are displayed on the x-axes, with blue marks indicating frost months and light blue marks indicating probable frost months. The red curve shows the temperature, the blue curve precipitation.

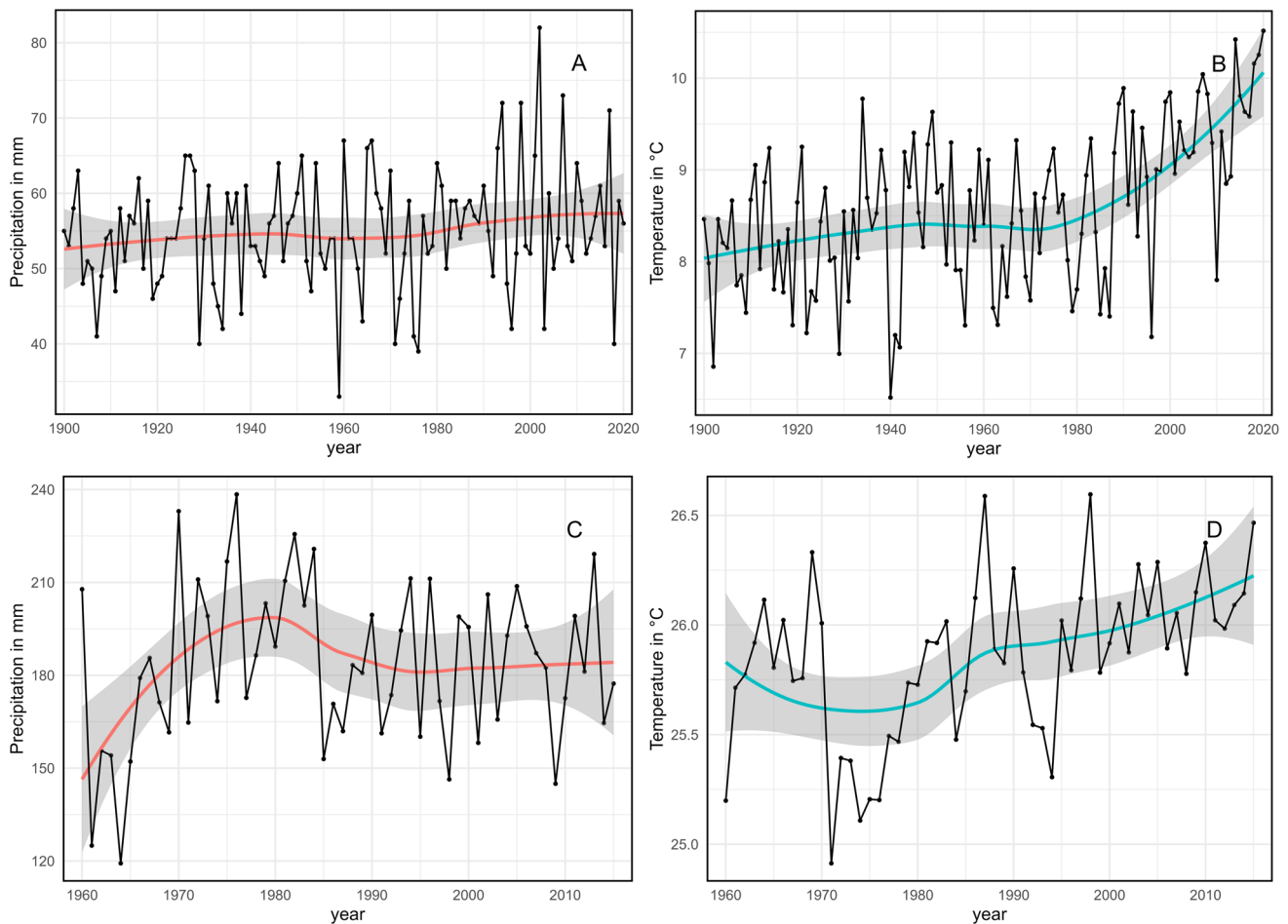
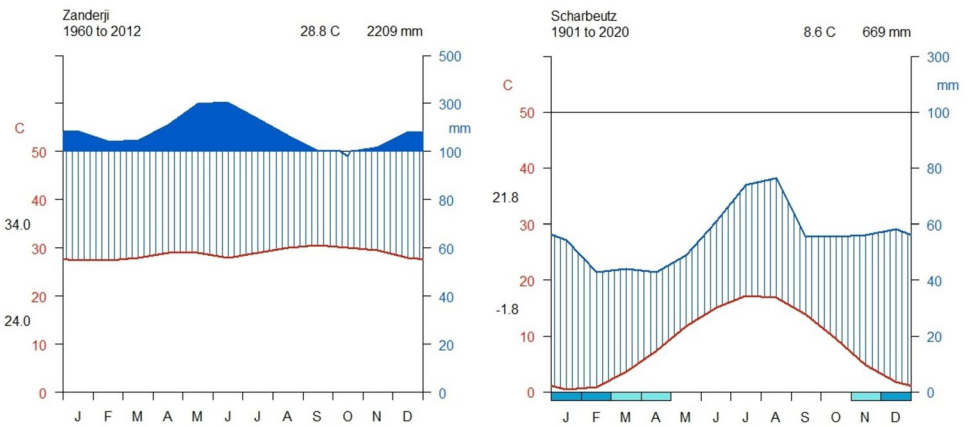


Fig. 3 Annual mean precipitation and temperature values for Scharbeutz (A, B) and Zanderij (C, D) for the respective time period.

Features in RF can be numerical or categorical data. When splitting the data at the nodes, classification trees aim for the split resulting in the best node purity. This means, that at each node, the data gets split into most homogeneous regions. In regression tasks, like the one used in this paper, each possible split of every feature is evaluated to minimize the Mean Squared Error (MSE). In each bootstrapped subset of the training data, about one third of the data is not

included, referred to as “out-of-bag” (OOB). This data is used to calculate the Generalization Error, by testing each classifier on the training data, but only on the respective OOB-samples. The R implementation of the RF algorithm was used for this paper (Breiman 2001). To consider for the algorithm’s variability, RF was run 100 times for each stand chronology and the respective variable importance for all input variables over every run was collected. The tuning

parameter *mtry* was left at its default value of 1/3 *m* as this provided the lowest MSE. The number of tree predictors *ntree* was kept at its default value of 500 as, while computing time was no issue, a larger *ntree* value provided no better results. Changes in the terminal node size or number did not improve the model's performance, so these values were kept at their default value as well. We also tested time series cross-validation (TSCV) as an alternative to OOB validation. In TSCV, the training data consists of data from an earlier period, with the validation data following chronologically (Hyndman and Athanasopoulos 2018). While Breiman (2001) and Genuer and Poggi (2020) state that OOB results are as good as cross-validation results in general, TSCV is particularly suited for time series data like the dataset present. We used the *timeslice* function from the R package *caret* (Kuhn 2008) with an initial window of 90 and a horizon of 10 on the three coniferous species. For Cedro, regarding the smaller sample size, we used an initial window of 40 and horizon of 5. As before, the importance value was collected across 100 runs.

Variable importance

We used Increase in Mean Square Error (IncMSE) as metric to describe the variable's influence on the RF model. IncMSE is the percentage change of the model's prediction precision on the OOB dataset if the respective variable is permuted randomly (Genuer and Poggi 2020). Respectively, in TSCV, the prediction precision is tested on the rolling window validation data (Hyndman and Athanasopoulos 2018). Variables with importance values above 0 increase the accuracy of the regression, while negative values imply that there is no positive effect of including the variable or rather leaving the variable out of the model increases the accuracy. Other studies used a selection process to omit negative or low importance variables (Fox et al. 2017; Janitza et al. 2018), but for better comparison with the RFA we decided to keep the low IncMSE variables. Contrary to the RFA, there is no indication about the sign of the correlation between the variable and the ring width index in the IncMSE value.

Accumulated local effects

Accumulated Local Effects (ALE) represent a method to visualize the effects of predictor variables in supervised learning models like RF (Apley and Zhu 2020) and are an alternative to the more commonly known Partial Dependence (PD). Apart from being less computationally expensive, ALE produce better results than PD when features are correlated. PDs show the average prediction of a model when one input feature is changed while the other features

are kept constant at their average value (Friedman 2001). With correlated features however, this might result in unrealistic results when PD uses artificial data instances that are unlikely to occur in reality (e.g. high precipitation on a day with no cloud cover). ALE on the other hand splits the data into intervals. For each data point within an interval, the feature gets replaced by the upper and the lower limit of this interval. The model predicts a value for both of these instances, and the difference between the two predictions gets calculated. Then, the average difference for all data-points within this interval is calculated. This is the effect the feature has on the average prediction in this local interval. The local intervals then get accumulated for easier visualization and centred, so that the average effect is zero. In this analysis, 20 intervals were used, which produced mostly smooth curves without losing much detail.

The ALE plot can be interpreted in a way that for each value of feature *x*, the average prediction of the model changes by the corresponding value on the *y* axis, the feature effect. Thus, ALE enables the user to reconstruct a feature's influence on the model predictions. This allows for the interpretation of the feature. A detailed and comprehensible explanation on ALE is given by Molnar (2022).

Results

Identifying impact variables

Figure 4 shows the results of the RFA and the RF variable importance values for spruce. The variable importance values of both OOB and TSCV are presented. The RFA identifies precipitation in the summer months June and July as the only climate variables significantly influencing growth ring increment. Accordingly, RF attributes these variables the highest importance values. May, April and March do not show significant influence at the 95% confidence interval, but nonetheless show a noticeable positive response coefficient, which is not reflected in the IncMSE value of RF. June precipitation of the previous year shows a nonsignificant, positive response coefficient, and a correspondingly increased IncMSE value. None of the mean temperature variables are significant in RFA for spruce, but March, May and September temperature show elevated coefficient values. In RF this is reflected in high importance values in March and May temperature, but not in September temperature. Additionally, the inclusion of February and July temperature increase the RF models' accuracy, which is hardly reflected in the RFA.

Multiple variables show a negative importance value for the RF analysis. Their respective coefficient values in RFA approximate zero, but show no obvious irregularities that

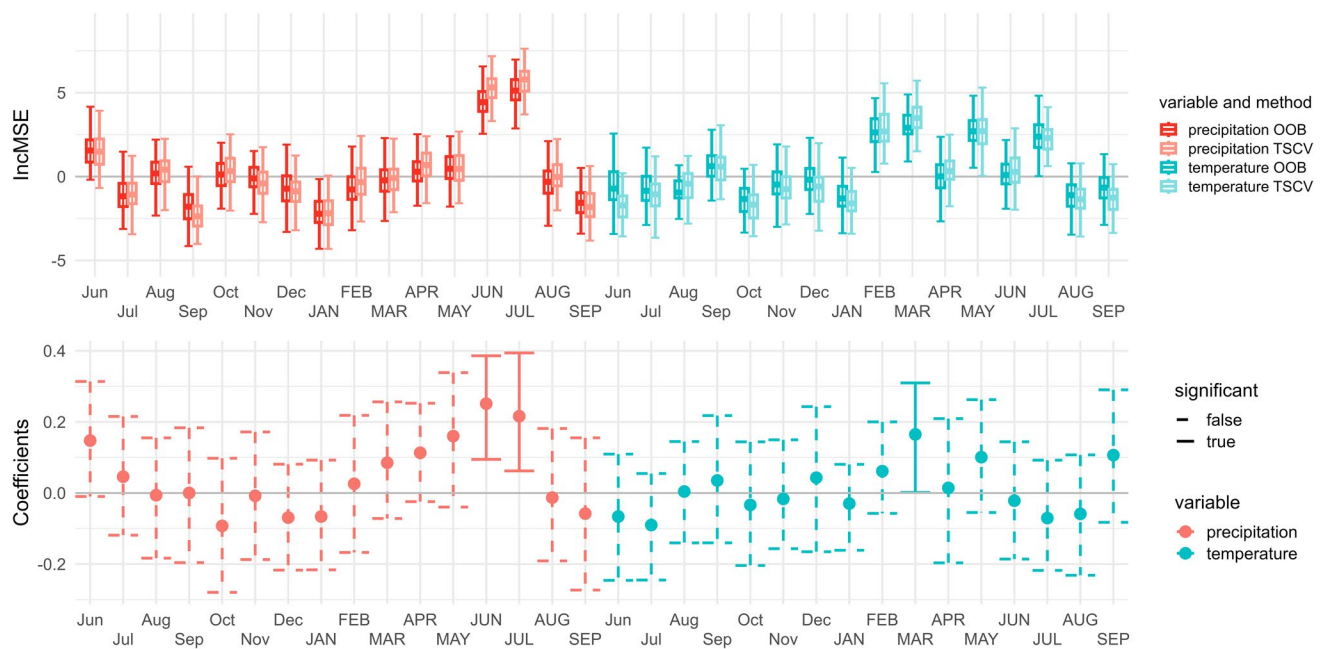


Fig. 4 Spruce distribution of importance value of variables of all 100 iterations (upper graph) and response coefficient (lower graph) for precipitation (red) and mean temperature (blue) for the period of 1906 to 2020. Significant values in RFA are represented by a solid line. previ-

ous year's months are abbreviated in lowercase letters, current year's months in capital letters. OOB importance values are represented by the darker shade, TSCV values by the lighter shade.

would further explain the negative influence on the RF models' performance. OOB importance and TSCV importance show little differences throughout the variables, not only for spruce but for the following species as well. The respective value with the highest importance value is more prominent in TSCV for all species.

For the Douglas chronology, the RF models reflect well the temperature influence established by the RFA (see Fig. 5). January mean temperature shows a particularly high importance value, followed by March temperature, and to a lesser extend February temperature as well. TSCV importance for February temperature is noticeably lower than the OOB value. Still, the positive coefficient is prominent in all respective variables. June temperature shows a significant negative correlation in RFA. The IncMSE value shows that this variable increases the models' accuracy, but does not show a strikingly high value. The same is true for the significant response coefficient of July precipitation. While the importance value is elevated, the January IncMSE value is higher, even though there is no prominent correlation for this variable in RFA. September precipitation shows a close-to significant correlation in RFA, but the IncMSE value is negative. Even if some of the variable's magnitude are evaluated differently by the models, RFA and RF seem to agree on the relevance of most variables.

For pine (Fig 6), similarly, the early year temperatures are identified as significant for growth ring width in the RFA. The RF models reflect this with high IncMSE values

for each respective early year temperature variable, with February temperature being outstanding. May temperature shows significant positive response coefficients, and June temperature shows a clear negative signal. RF attributes both of these variables a high significance, with June being above the May value. Interestingly, for mean temperature, only July and both years' September temperature negatively influence the RF models' performance, while for the other coniferous tree species a fair proportion of variables have IncMSE values below zero. Previous years' November temperature positively affects the RF models' accuracy while it seems to have no climate signal in the RFA. The same applies to February precipitation. Looking further at the precipitation values, May and July are significant in the RFA as reflected in the IncMSE. A positive, nonsignificant RFA correlation to April precipitation is not reflected in RF. Effects of the other months are less pronounced, but seem to be well aligned between the two approaches, with the occurrence of negative IncMSE values being as frequent in precipitation as in the other tree species results. Again, OOB and TSCV importance show little difference.

Figure 7 shows the RFA results and RF variable importance values for Cedro, including all monthly mean precipitation and temperature values from previous year's January to current year's December. For Cedro, the growth ring formation most likely takes place at the beginning of the long dry period from September to October. For mean temperature, RFA shows no significant correlation with

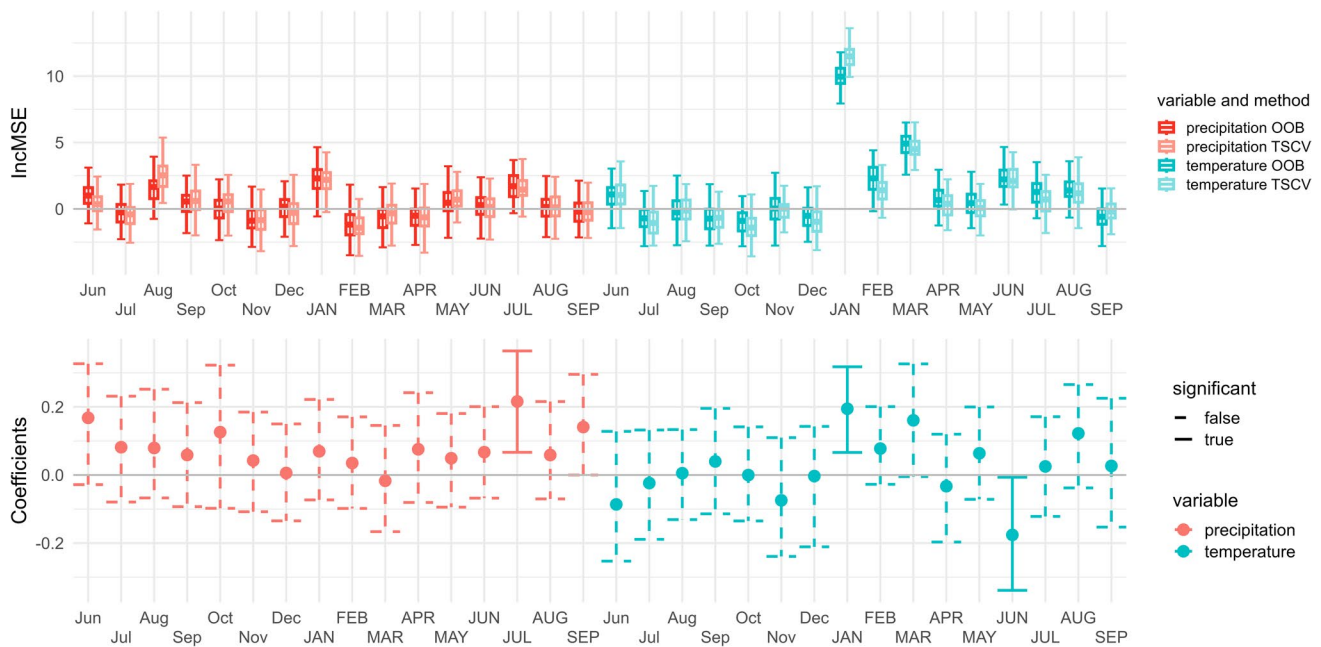


Fig. 5 Douglas distribution of importance value of variables of all 100 iterations (upper graph) and response coefficient (lower graph) for precipitation (red) and mean temperature (blue) for the period of 1906 to 2020. Significant values in RFA are represented by a solid line. Previ-

ous year's months are abbreviated in lowercase letters, current year's months in capital letters. OOB importance values are represented by the darker shade, TSCV values by the lighter shade.

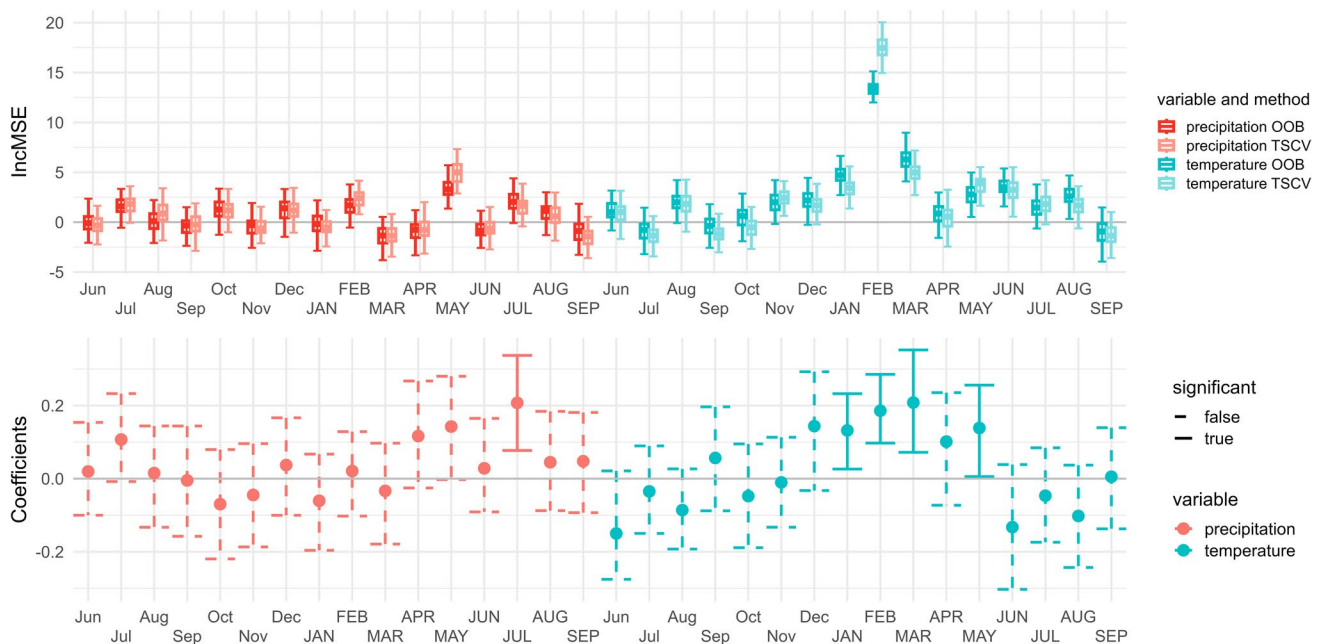


Fig. 6 Pine distribution of importance value of variables of all 100 iterations (upper graph) and response coefficient (lower graph) for precipitation (red) and mean temperature (blue) for the period of 1906 to 2020. Significant values in RFA are represented by a solid line. Previ-

ous year's months are abbreviated in lowercase letters, current year's months in capital letters. OOB importance values are represented by the darker shade, TSCV values by the lighter shade.

ring width increment. The strongest coefficients for temperature show a positive correlation for November and previous years March temperature, and a negative correlation for previous years November temperature. The RF

models attribute negative IncMSE values to all temperature variables, indicating that there is no explanatory power of these values for these models. However, both approaches show a correlation between growth ring width and multiple

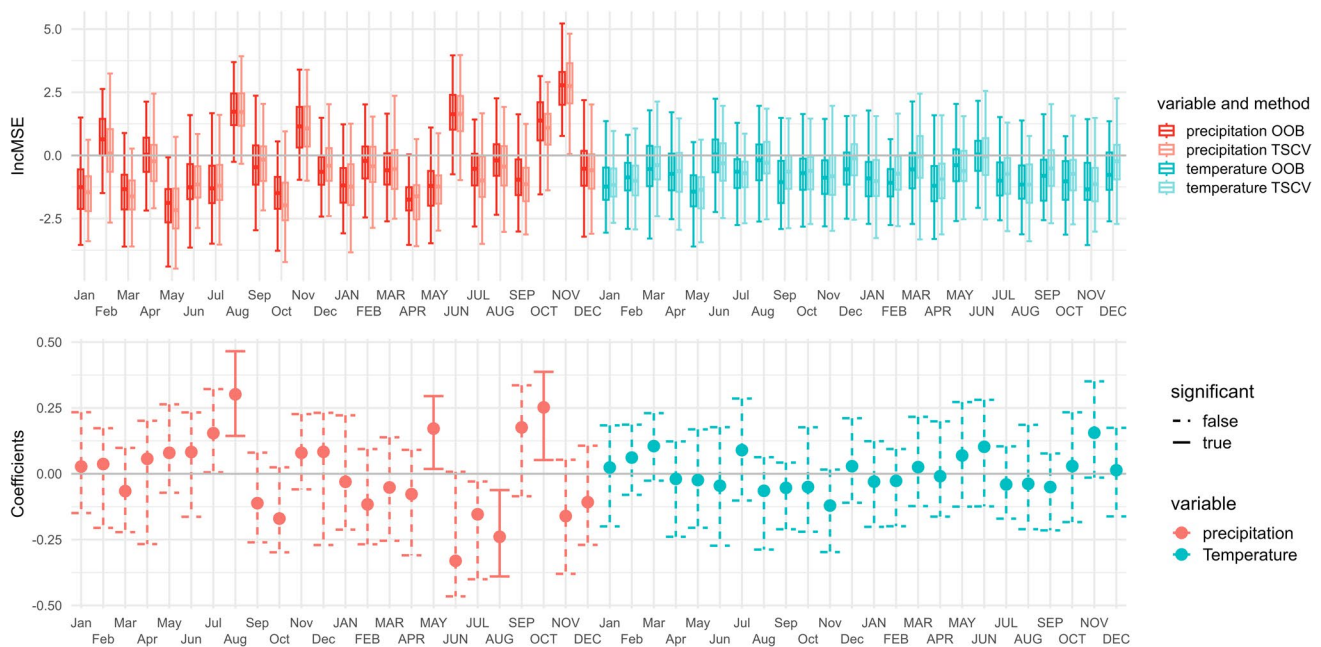


Fig. 7 Cedro distribution of importance value of variables of all 100 iterations (upper graph) and response coefficient (lower graph) for precipitation (red) and mean temperature (blue) for the period of 1960 to 2015. Significant values in RFA are represented by a solid line. Previ-

ous year's months are abbreviated in lowercase letters, current year's months in capital letters. OOB importance values are represented by the darker shade, TSCV values by the lighter shade.

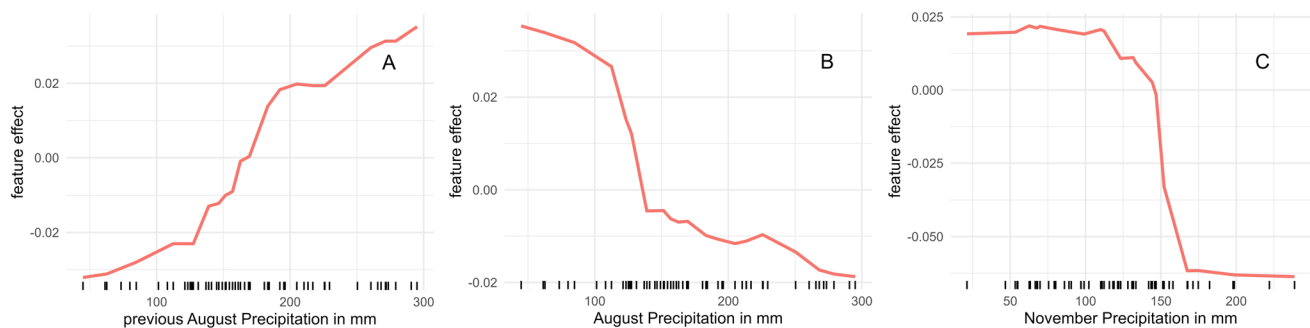


Fig. 8 ALE plots for Cedro for previous year's August precipitation (A), August precipitation (B) and November precipitation (C). The rug at the x-axis represents the data instances for the respective variable.

months precipitation. Previous year's August precipitation and current year's October precipitation both have significant correlation in RFA, backed by a high IncMSE value in RF. The two other significant response coefficients however, that are May and August precipitation, show no IncMSE value that would indicate a climate relation. Further variables with high importance values are previous year's November precipitation, June precipitation and November precipitation. These variables have a respectively high (or highly negative), but nonsignificant response coefficient. For other variables, that have a distinct, but nonsignificant response coefficient, the IncMSE value does not reflect the RFA result, namely previous year's July and October, and current year's July precipitation.

Detailed variable impact

Looking into the ALE plots (Fig 8) of some of the climate variables for Cedro gives more detailed information on the growth conditions. The previous year's August precipitation (A) shows a close to linear effect on the model's prediction, with a slight inflection point around 150 mm monthly precipitation, indicating that a longer precipitation period before the next dry season helps secondary growth in the following growth period. The current year's August precipitation (B) is inversed to this, but with a clear drop in feature effect when precipitation exceeds around 100 mm. November precipitation (C) again shows a negative effect on monthly precipitation above a threshold at around 150 mm.

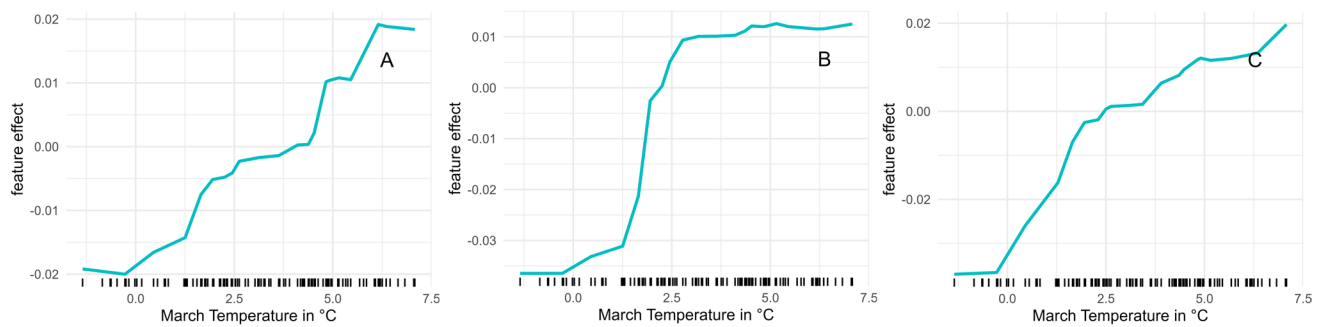


Fig. 9 ALE plots for March mean temperature for spruce (A), Douglas (B) and pine (C). The rug on the x-axis represents the data instances for the respective variable.

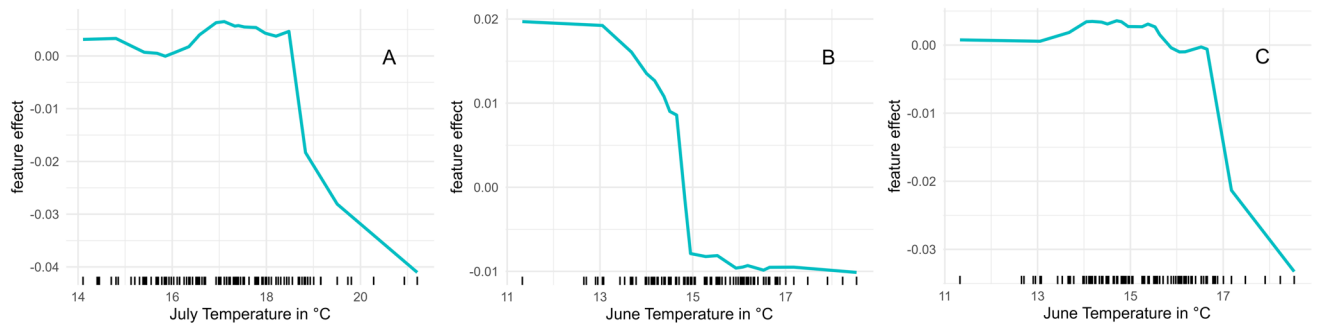


Fig. 10 ALE plots for July mean temperature for spruce (A) and June mean temperature for Douglas (B) and pine (C). The rug on the x-axis represents the data instances for the respective variable.

Figure 9 shows the ALE plots for March mean temperature for the three coniferous species from Scharbeutz. This variable showed high IncMSE values in all RF models and a distinct response coefficient for each RFA, with a significant value for pine. All ALE plots show a positive correlation of temperature and growth, in line with the RFA. The ALE curves for spruce (A) and pine (C) have very similar appearances, with a close to linear correlation between March mean temperature and ring width. For Douglas (B), there is a strong increase in slope at a mean temperature above roughly 1.25°C, flattening out around 2.5°C. For all three species, the feature effect for mean temperatures below 0°C remains steady at a negative value, which could be interpreted as frost having the same negative impact regardless of its intensity. Note that the number of sample points decreases towards the axis limits, so the validity has to be regarded with caution.

The ALE plots in Fig 10 show the influence of the most impactful summer temperatures on the RF model for each species, namely June temperature for Douglas (B) and pine (C) and July temperature for spruce (A). All three curves have in common that they seem to plateau until a certain temperature threshold, where a steep incline in feature effect occurs. For Douglas this decline seems to happen between 13 to 15°C with a comparatively gradual decline, while for pine, the decline begins at about 16 to 17°C. Mean temperature in July seems to negatively affect spruce growth when

it reaches above 18 to 19°C. Both the spruce and the pine graph show a maximum just before the decline, indicating an optimum mean temperature for ring width increment in the respective month.

The left curve in Fig 11 shows the ALE of June mean temperature for spruce (A). Contrary to the other two coniferous species, neither the RFA nor the RF importance attributed a high impact on ring width to this variable. While the ALE does implicate a positive effect of this variable, the feature effect amplitude is substantially lower than on variables with a higher IncMSE value. Adding to this, the trend of the curve is irregular, while the previously regarded ALE showed a more or less consistent effect of changes in the respective variable. The variable B of Fig 11, Douglas September precipitation, has been attributed a positive correlation in RFA, while RF importance was below zero. The ALE again show an irregular curve while having a clear positive trend. The strong linearity of the effect on precipitation values above 100 mm has to be put into perspective regarding the small sample size in this range, resulting in large local intervals. Pine February temperature (C) showed the largest importance value in all four analysis. Similar to the March ALE (Fig 9, C), a mean temperature below 0°C has a constant negative effect that does not increase with lower temperatures. It is only around -1°C that a higher temperature has a strong positive effect on ring width. Interestingly, there seem to be two saddle points in the ALE curve, the

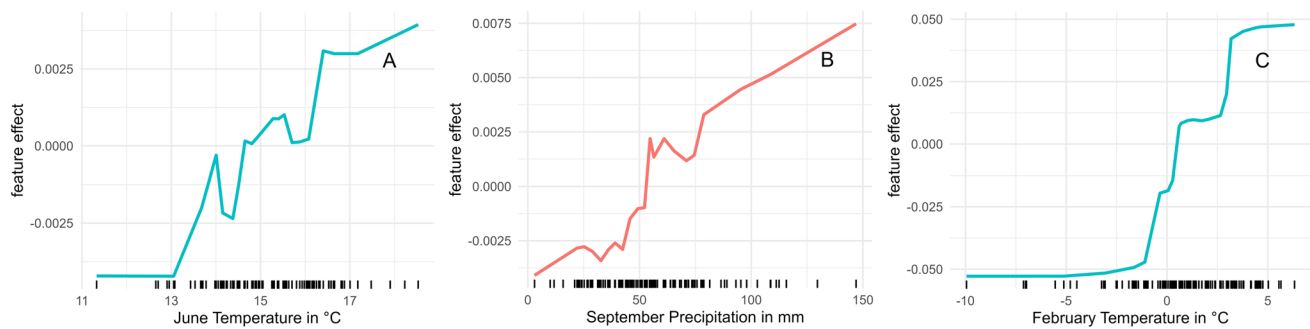


Fig. 11 ALE plots for June mean temperature for spruce (A), September precipitation for Douglas (B) and February mean temperature for pine (C). The rug on the x-axis represents the data instances for the respective variable.

first being at zero degrees and the second being in the range between 0 and 2.5°C, before the curve plateaus at temperatures over 3°C. It is unclear whether these plateaus have an underlying physiological cause, or are a result of the split wise nature of the RF algorithm. The high number of data instances in this range supports the former interpretation.

Discussion

The comparison of coefficient values in RFA and IncMSE values in RF importance shows a good alignment for many instances and discrepancies for some. Across all species, 15 input variables were categorized as significant at the $P=0.05$ level in RFA, of which 13 have high IncMSE values for the respective month. For the coniferous species, all 11 occurrences of significant variables in RFA have a respectively high IncMSE value. There are two cases where RF attributes no high importance value to a variable significant in RFA—May and August precipitation for Cedro. The ALE plot for these two variables show the current year's effect inverse to the previous year's effect. Fritts (1976) explained that prior growth values can inverse the effect of prior year's climate variables. When a high August precipitation leads to reduced ring width in this year, and narrow rings are generally being followed by wider rings, it appears that previous years precipitation has a positive correlation, as seen in this analysis. However, this should have no substantial effect on the importance value. Due to the random feature selection at each split when constructing the predictor tree, a share of the forest's decision trees is created without one or the other variable. Consequently, no feature's importance value is reduced by another feature. As the ALE plots still show the same correlation sign as the RFA, the model simply evaluates the variables impact differently. In a RFA conducted by Köhl et al. (2022) on the same Cedro dataset and time-frame, precipitation values for both August features showed significant impact, as well as current year's June precipitation. Venegas-González et al. (2018) found significant

precipitation influence for Cedro stands in southern Brazil before, at the beginning, and in the middle of a growing season, depending on the stand.

Contrary to this, in the present study, November precipitation of the current year had the highest IncMSE value in RF for Cedro and a distinct, nonsignificant value in RFA. As ring formation should be concluded after the dry season, November precipitation should have no direct impact on growth ring width—or, if high November precipitation was linked to wet dry season months, one would expect a positive correlation as observed in September and October. The low sample size in the high precipitation range, in combination with the steep incline observed in the ALE plot, could be a hint that the apparent variable influence is coincidental. This draws the question whether this conclusion casts doubt on the considered coniferous ALE plots that show a similarly steep decline. While data points for spruce July—and pine June temperature are sparse in the high temperature range, the incline for Douglas June temperature takes place in a range with numerous datapoints. Moreover, summer mean temperature thresholds have been found in several other studies on temperate conifer trees (e.g. D'Arrigo et al. 2004; Sidor et al. 2015; Piovesan et al. 2023) and can be attributed to the exceedance of the physiologically optimal conditions (Huang et al. 2019). The plausible March temperature effects, where an increase in ring width occurs when mean temperature reaches above 0°C, affirm the potential of this method to replicate climate signals. Low importance variables in RF result in ALE plots with irregular curves, and the overall contribution to the model is limited. The respective correlation coefficients in RFA are often close to zero, confirming the negligible impact of these variables. The results of Gauli et al. (2022), who applied RFA on the same stand, closely match the present RFA, confirming the results of this analysis.

Strobl et al. (2007) states that variable importance in RF is biased towards strongly correlated features. While there will always be a certain correlation between climate variables, this effect should not affect the results of this study.

Genuer et al. (2010) examined the effect of correlated variables on variable importance. While the total values of variable importance change when adding correlated variables to a model, the order of important variables stays unaffected. Potential correlation between the variables thus does not change the interpretation of this study's results, as only relative values were regarded instead of total values.

Autocorrelation in the data can also lead to spurious correlations and data leakage. Correlations found by RF should therefore always be carefully examined for their plausibility. For this dataset, with a reasonable time-span and a relatively simple climate-growth structure, TSCV did not yield importance values substantially different from the OOB dataset. The highest importance feature was even more prominent in all species, while the other important features showed slightly lower values accordingly. TSCV can still be worth considering in datasets with stronger temporal autocorrelation, where the results likely would differ more noticeably.

A downside of RF in contrast to RFA is the lack of information on variable significance—even though approaches for variable selection and importance measures exist (Hapfelmeier and Ulm 2013; Janitza et al. 2018), importance values do not allow for any conclusion on statistical significance. Cook and Pederson (2011) discuss the role of statistics in dendrochronology. They highlight the fact that the α -level for statistical significance, 0.05 in this and in many other papers, is determining the probability of Type-1 and Type-2 errors. Thus, information on significance is vital to evaluate the reliability of alleged correlations, but non-significance at a certain level does not rule-out any possibility that there is in fact a biological correlation hidden in the data. Here, ALE plots enable for further analysis of these features, which allows both for plausibility checking of correlations and information gain on nonlinearity in those relationships. This underlines the point that RF can be used as powerful tool for gathering information in exploring climate-growth relations and finding physiological backgrounds of statistical correlations in dendrochronological data. Future applications can expand on the advantages of RF, like the inclusion of categorical features such as soil type.

Conclusion

Tree ring analysis provides valuable insight into past tree growth. In connection with records about the growth conditions, for instance climate data, it can increase our understanding of the physiological responses of trees and thus help us to predict future tree growth. While traditional methods as RFA work well to identify relevant variables, machine learning approaches like RF can deliver comparable results,

but furthermore add more detailed information on the qualitative effect of individual variables. Using ALE revealed nonlinear climate-growth responses for several climate variables and helped in evaluating unexpected correlations. While, especially for the coniferous species results, the variable importance was in good alignment with RFA, the strength of the approach lies in the further analysis of the data. Using a combination of the methods is recommended to consider potential deviations and make use of the easy interpretability of RFA results, but taking advantage of the additional information RF can provide.

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Data availability The formatted datasets and the respective code used in this article are available from the corresponding author on reasonable request.

Declarations

Competing interests The authors declare no conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript, or in the decision to publish the results.

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