Analyzing the effects of stand thinning on microclimates with semiparametric smoothing splines

Biing T. Guan, Shih-Hao Weng, Shing-Rong Kuo, Tsung-Yi Chang, Hsin-Wu Hsu, and Chieh-Wen Shen

Abstract: Monitoring the effects of stand thinning on microclimates is an integral part of any thinning experiment. It is through its modifications of microclimates that thinning alters important ecological processes. An efficient analysis of microclimate-monitoring data should address both the effects of thinning regimes on, and the temporal response trends of, microclimates. Probably because of the difficulties in modeling temporal trends parametrically, an examination of the existing literature on thinning showed that only a few studies have attempted to address the second aspect. We propose the use of semiparametric smoothing splines to analyze monitoring data from thinning experiments. First, the concept of a smoothing spline is briefly described. We then provide an example in which semiparametric mixed-effects smoothing-spline models were used to analyze microclimate-monitoring data from a thinning experiment. The proposed approach not only successfully detected the effects of thinning, but also revealed interesting temporal trends. For each of the microclimatic variables, we also compared the performance of the fitted semiparametric model with that of a parametric model. In general, the semiparametric model performed better than its parametric counterpart. We also address some concerns in using the proposed approach.

Résumé : Le suivi des effets de l’éclaircie sur le microclimat fait partie intégrante de toute expérience d’éclaircie, car c’est en modifiant le microclimat que l’éclaircie affecte des processus écologiques importants. Une analyse efficace des données de suivi du microclimat devrait considérer à la fois l’influence du régime d’éclaircie sur le microclimat et les tendances temporelles de réponse du microclimat. La littérature sur l’éclaircie montre que peu d’études ont essayé d’aborder le second aspect, probablement parce qu’il est difficile de développer des modèles paramétrés pour les tendances temporelles. Les auteurs proposent l’utilisation de splines de lissage semi-paramétriques pour analyser les données de suivi provenant de dispositifs d’éclaircie. Le concept d’une spline de lissage est d’abord brièvement décrit. Ils fournissent ensuite un exemple dans lequel des données de suivi du microclimat provenant d’un dispositif d’éclaircie ont été analysées à l’aide de modèles de splines de lissage semi-paramétriques à effets mixtes. L’approche proposée a non seulement détecté les effets de l’éclaircie avec succès mais elle a également révélé des tendances temporelles intéressantes. Pour chaque variable microclimatique, ils ont aussi comparé les performances du modèle semi-paramétrique ajusté et d’un modèle paramétrique. De façon générale, les modèles semi-paramétriques étaient plus performants que leur contrepartie paramétrique. Ils ont également abordé certaines préoccupations concernant l’utilisation de l’approche proposée.


Introduction

Many large-scale thinning experiments have been undertaken around the world during the past decade to understand the effectiveness of stand thinning in promoting the biodiversity and sustainability of plantation forests (Sullivan et al. 2001; Monserud 2002; Muir et al. 2002; Hagar et al. 2004; Harrison et al. 2005; Sullivan et al. 2005). Monitoring the effects of thinning on microclimates is an integral part of any thinning experiment. It is through its modifications of microclimates that thinning alters important ecophysiological and ecosystem processes (Aussenac 2000; Thibodeau et al. 2000; Baudhus et al. 2001).

Analyzing the microclimate-monitoring data from a thinning experiment has two objectives. The first objective is to compare the effects of different thinning regimes (e.g., thinning intensity) on the microclimates. This calls for an analysis of variance (ANOVA)-like approach. The second objective is to identify temporal trends in important microclimatic variables. This requires a time-series- or regression-like approach. An analysis of covariance (ANCOVA) approach is a natural choice to achieve both objectives simultaneously. With such an approach, we regard the thinning regime as a discrete explanatory variable and time as a continuous explanatory variable.
A survey of the thinning-experiment literature showed that ANCOVA has rarely been used in analyzing microclimate-monitoring data. Although all thinning studies analyzed the effects of thinning regime on the monitored microclimatic variables, only a few studies attempted to reveal the temporal trends of these variables (e.g., Prévost and Pothier 2003). Some studies provided only the arithmetic means and standard errors of microclimatic responses. We believe that this failing is due mainly to the difficulty in modeling nonlinear temporal trends.

Another issue that we need to consider in analyzing monitoring data is their longitudinal nature. Parametric mixed-effects modeling is one of the statistical approaches that could be used to account for autocorrelations (Gregoire et al. 1997). With parametric mixed-effects modeling, we can account not only for correlations (both temporal and spatial), but also for random variations among the monitoring points, as well as other data structures (e.g., heteroscedasticity) in the monitoring data. Although parametric mixed-effects modeling is well developed (e.g., Pinheiro and Bates 2000), the difficulty of specifying an adequate model for temporal trends would likely limit its use. Another possible approach is to adopt some form of nonparametric regression with which to model nonlinear temporal behaviors.

Motivated by Verbyla et al. (1999), we propose the use of a semiparametric mixed-effect modeling approach based on the smoothing splines of Wahba (1990) to analyze the effects of thinning on microclimates. We first briefly describe the idea of a smoothing spline. We then provide an example from a thinning experiment conducted in Taiwan. For each of the microclimatic variables, we also compare the performance of the semiparametric model with that of a parametric model. Finally, we discuss some considerations and cautions in using the proposed approach.

### Smoothing splines

A smoothing spline can be viewed as a compromise between a model’s ability to fit data and the model’s smoothness (i.e., the bias–variance trade-off; Green and Silverman 1994). A smoothing spline can also be viewed as a compromise between using a constant slope to fit all data (i.e., a least-squares linear regression) and using a set of slopes, defined by any two points, to fit all data (i.e., connecting data points; Eubank 2000). For a more formal explanation, let \( f(x) \) be a smooth function that we use to approximate a set of data from some interval \([a, b]\), and \( a < x_1 < x_2 < x_3 < \ldots < x_n < b \). Then a polynomial smoothing spline is the solution that minimizes the residual sum of squares (RSS) function having the form

\[
\frac{1}{n} \sum [y_i - f(x_i)]^2 + \lambda \int_a^b |f^{(m)}(x)|^2 \, dx
\]

where the first term defines the goodness of fit of \( f(x) \), the second term is the smoothness of \( f(x) \) (represented by the squared integral of the \( m \)th derivative), and \( \lambda \) is a smoothing parameter (Wahba 1990; Green and Silverman 1994; Eubank 1999). Because of the second term in the RSS function, a smoothing spline is also known as a roughness-penalty approach (Green and Silverman 1994).

The smoothing parameter, \( \lambda \), is a measure of the trade-off between a good fit and the smoothness of \( f(x) \). When \( \lambda \) tends to infinity, the smoothness component of RSS will be the dominant term, and the fit will approach a least-squares linear fit, since no curvature is allowed. When \( \lambda \) approaches 0, the main contribution to RSS will then be from the goodness-of-fit component, and the fit will essentially be interpolating between data points (i.e., a rough function without any smoothing; Green and Silverman 1994).

The main idea of a smoothing spline is to find a suitable \( \lambda \) value such that the approximating function is smooth (with less variance) but still fits the data closely (with less bias). Figure 1 provides a simple example to explain the idea. A polynomial smoothing spline can be viewed as a set of piecewise polynomials joined together at unique data points. For example, if \( m = 2 \) (i.e., twice differentiable), then \( f(x) \) is the well-known cubic smoothing spline. This particular smoothing function, \( f(x) \), satisfies the following two conditions: (1) at each of the intervals \((a, x_1), (x_1, x_2), (x_2, x_3), \ldots, (x_{n-1}, x_n), (x_n, b)\), \( f(x) \) is a cubic polynomial, and (2) the set of piecewise cubic polynomials are joined at \( x_i \) such that \( f(x) \) and its first and second derivatives are continuous at each \( x_i \).

The approximating function, \( f \), will therefore be smooth through the entire interval \([a, b]\) (Green and Silverman 1994). Besides polynomial splines, we could also use other smoothing-spline methods (e.g., periodic splines, thin-plate splines; Wahba 1990; Gu 2002) to approximate complex behaviors.

The most critical issue in fitting a smooth spline is choosing a proper smoothing parameter. Data-driven automatic methods for finding an “optimal” smoothing parameter include the generalized cross-validation method (Craven and Wahba 1979) and the generalized maximum likelihood method (Wahba 1985). Many smoothing-spline computer programs have implemented one or both selection methods. Detailed explanations of the methods can be found in the references cited. Wood (2001) provided an explanation of the smoothing spline and the generalized cross-validation method in an ecological modeling context.

The advantage of using a smoothing spline is in the method’s ability to approximate the underlying nonlinear function closely without the need to specify exactly the form of the approximating function. Thus, the approach is nonparametric. In Fig. 1, the fitted smoothing-spline curve approximates the underlying function adequately.

In recent years the basic smoothing-spline approach has been extended to model the data semiparametrically and to accommodate mixed effects, correlations, heteroscedasticity, and other variance structures in the data (Wang 1998a, 1998b; Verbyla et al. 1999; Gu 2002; Wang and Ke 2004). Such extensions allow smoothing splines to analyze complicated data structures. While applications of smoothing splines are gaining popularity in forestry and ecological research (e.g., dendroecology (Pederson et al. 2004; Larocque and Smith 2005) and ecology (Wood 2001)), they are mainly used in a nonparametric fashion.

### Example

#### Descriptions

The example is taken from a comprehensive thinning project in Taiwan. The main objective of the project had been to
promote the biodiversity of even-aged plantation forests in Taiwan. The data were from a thinning experiment conducted in a 30-year-old Japanese cedar (or sugi, Cryptomeria japonica (L. f.) D. Don) plantation located in the Guanwu area (24°30′N, 121°07′E, elevation between 2000 and 2200 m a.s.l.) of northern Taiwan. The average annual temperature in the study area is approximately 12.1 °C (6.3 °C in January, 16.2 °C in July) with average annual precipitation of about 3200 mm.

Three thinning intensities (strong, moderate, and weak) and a control (unthinned) were used in the experiment. The experimental area was about 40 ha and the treatment areas varied from 5 to 14 ha. The aspect of the study area was mainly northwest, except for the moderately thinned stand, where it was north. The experiment was unreplicated, owing to operational constraints. All thinning treatments used the traditional thinning-from-below approach. The thinning experiment was conducted from October to December 2001. The average numbers of residual stems and average residual basal areas (in parentheses) per hectare after thinning were 500 (32.2 m²), 680 (53.0 m²), 960 (70.8 m²), and 1540 (82.8 m²) for the strong, moderate, and weak treatments and control, respectively.

Microclimate monitoring

In January 2002, four monitoring points were established for each treatment. Recording devices were set up at each point to record a set of microclimatic variables every 2 h. The variables included air temperature (AT), soil temperature (ST), soil water potential (SWP), and relative humidity. From the two temperature variables, two additional variables were derived: air-temperature range (ATR) and soil-temperature range. In this example, only the monthly average AT, ST, ATR, and SWP from each of the 16 monitoring points are presented; the soil-temperature range and relative humidity are not included because they can be better modeled by parametric mixed-effects models. The monitoring period used in this example was February 2002 to January 2004 inclusive. It should be mentioned that during this period, the study area experienced the driest 2-year period ever recorded.

Semiparametric smoothing-spline models

The proposed approach can be viewed as a semiparametric ANCOVA approach. Under the proposed approach, thinning intensity is the discrete, parametric part, whereas time is the continuous, nonparametric part mainly modeled by smoothing splines. The effects of thinning intensity averaged over the entire monitoring period can be assessed by parametric F or t tests, just like the regular ANCOVA approach.

The semiparametric models used to analyze the four variables are summarized below. They represent the models that were judged to provide the best fit. The computer package used was the assist package (Wang and Ke 2004) of R (R Development Core Team 2005). This package is built onto the nlme package (Pinheiro et al. 2005) of R. Owing to a software constraint, the smoothing parameter was estimated by the generalized maximum likelihood method. It was assumed that the errors were independently and identically distributed as $N(0, \sigma^2)$. To satisfy this assumption, correlations and heteroscedasticity in the residuals were accounted for by the approaches given in Pinheiro and Bates (2000, Chap. 5). The residual diagnostics indicated that the residuals from all the fitted models did not significantly violate the assumptions.

Models for AT and ST

For these two variables, we used a cubic smoothing spline

Fig. 1. An example of using a smoothing spline to approximate a cosine function. (a) The solid points were from \( \cos(x) \) with added random noises from a uniform (–0.3, 0.3) distribution. The broken smooth curve is from a smoothing spline. The solid straight line is the least-squares fitted linear-regression line. The broken-line segments connecting the data points represent the fitted model when the smoothing parameter approaches 0. (b) The fitted values from a smoothing spline versus the corresponding noise-free values from \( \cos(x) \). The broken line is a 1:1 fit.
to model the temporal trends. In R syntax, the models can be expressed as \( at \) (or \( st \)) \~\( thin + cs(t) \), where \( thin \) represents thinning intensity and \( cs(t) \) represents a cubic spline in time, with the time factor \( t \) rescaled to between 0 and 1. We used the smoothing-spline regression (ssr) function of \textit{assist} to analyze the data, with a continuous AR(1) process to account for the autocorrelations.

**Model for ATR**

Since the data displayed large variation among the four monitoring points for each of the treatments, we treated the four monitoring points for each treatment as a random effect. The parametric parts included thinning intensity and an interaction term between the linear temporal trend and thinning intensity. A periodic smoothing spline was used to model the temporal trend. This part of the model can be expressed as \( atr \sim thin + thin \cdot t + periodic(t) \), where \( thin \cdot t \) represents the interaction term and \( periodic(t) \) is the periodic spline. A power function was used to account for heteroscedasticity in the data, and an AR(1) process was used to account for autocorrelations. The semiparametric linear mixed effects (slm) function of \textit{assist} was used to analyze the data.

**Model for SWP**

For SWP the parametric parts included thinning intensity and a linear trend in time. Monitoring points were treated as random. We used a periodic smoothing spline to model the temporal trend. This part of the model can be expressed as \( swp \sim thin + t + periodic(t) \). Heteroscedasticity within the data was accounted for by an exponential function. Correlation in the data was modeled by a MA(1) process. The slm function was used to analyze the variable.

**Parametric models**

For comparison, we also fitted a linear model for each of the four variables. For both AT and ST the models were ANCOVA models with the temporal trends modeled by a sixth- and a fifth-degree polynomial, respectively. We used higher order polynomials to model those two variables because we were unable to develop adequate nonlinear parametric models. For ATR the parametric parts included thinning intensity, linear and quadratic trends in time, an interaction term between thinning intensity and the linear temporal trend, and a temporal cyclic trend modeled by both sine and cosine functions (\( atr \sim thin + t + t^2 + thin \cdot t + \sin(t) + \cos(t) \)). For SWP the structural part of the model can be expressed as \( swp \sim thin + t + \sin(t) + \cos(t) \). For ATR and SWP, all monitoring points were treated as random. To account for correlations and variance structures, the generalized least squares (gls) function of the \textit{nlme} package was used to fit the AT and ST data, whereas the linear mixed effects (lme) function of the same package was used to fit the ATR and SWP data. For both AT and ST, an AR(1) process was used to account for autocorrelation. For ATR, a MA(2) process was used to model autocorrelation, whereas a power function was used to model heteroscedasticity. For SWP, heteroscedasticity was accounted for by a combination of exponential and power functions.

**Results**

**AT and ST**

ATs and STs displayed a similar pattern across the 24-month monitoring period (Figs. 2 and 3), and both reflected the temperature pattern recorded at the nearby Guanwu weather station. For both variables, the fitted semiparametric models agreed with the observed data. The correlation be-
between the fitted and the observed values for both models was 0.97. Results showed that over the 2-year period the average monthly AT at the strongly thinned stand was about 0.6 °C higher than at the control \((p < 0.05)\). The temperature differences between the other two thinning treatments and the control were not statistically significant. Strong thinning also resulted in a significantly higher ST than for the control \((p < 0.05)\).

**ATR**

For this variable the correlation between the semiparametric fitted and observed values was 0.81, suggesting that the model was appropriate. The fitted semiparametric model showed a prominent cyclic temporal trend for all treatments (Fig. 4). The weather records at the Guanwu weather station during the study period showed that average precipitation and ATR were negatively correlated \((\text{Pearson’s } r = -0.74, p < 0.001)\). Therefore, the trends reflected mainly the relationship between average monthly precipitation and ATR in the study region. Thus, in 2002, ATR declined steadily from spring until late summer (wet season), and then rose toward the end of that year. In 2003 the trend during the spring was similar. However, because of a severe summer drought in that year, ATR peaked in July and then declined again toward the end of the year.

Averaged over the 2-year period, ATRs for the thinned stands were all significantly higher than that for the unthinned stand \((p < 0.005\) for all the thinned stands). The strongly thinned stand exhibited the largest difference, followed by the weakly thinned stand. Over the monitoring period the strongly thinned stand also had a significantly higher ATR than the other two thinned stands. The significant \((p < 0.001)\) parametric interaction term between thinning intensity and time suggested that the downward rates varied among the treatments, with the strongly thinned stand having the highest downward rate, followed by the weakly thinned stand. The rates for the moderately thinned and control stands were about the same.

**SWP**

For this variable the correlation between the semiparametric fitted and observed values was 0.71, which suggested that the model fit was moderately satisfactory. The fitted semiparametric models all showed dominant downward trends from the summer of 2002 until the end of the monitoring period (Fig. 5). The downward trend reflected the drought conditions during that period. Among the four stands, the moderately thinned stand had the highest SWP, followed by the strongly thinned stand. The higher SWP for the moderately thinned stand was mainly due to its northern aspect. SWPs for the moderately and strongly thinned stands were significantly higher than that for the control \((p < 0.001\) and \(p = 0.044\), respectively). The fitted models showed significant cyclic trends, which reflected the relation between SWP and precipitation. An important feature of Fig. 5 is that all thinned stands had higher SWPs during the severe summer drought of 2003.

**Model performance and comparison**

Table 1 summarizes the model-fitting and performance information for the fitted semiparametric and parametric models for each of the microclimatic variables. The estimated smoothing parameters of the four semiparametric models were all small, suggesting that smoothing splines did contribute to reducing RSS. Judging from the model-performance criteria, the semiparametric models for AT and ST performed significantly better than their parametric counterparts. For ATR and SWP the semiparametric models also performed better. Except in the case of SWP, the semi-
parametric smoothing spline models also yielded smaller estimated error variances.

For AT and ST the trends revealed by both the semiparametric and the parametric models were similar (Figs. 2 and 3), but the fits from the semiparametric models were much closer to the observed trends. The semiparametric and the parametric models agreed concerning the effects of thinning intensity on AT. However, they disagreed on the effects of thinning on ST. The semiparametric model suggested that the only significant difference was between the strongly thinned and unthinned stands. In contrast, the parametric model suggested that, regardless of intensity, thinning would result in a significantly higher average monthly ST than that suggested by the semiparametric model. In our example, the four response variables all exhibited complex nonlinear temporal trends, and the flexibilities and capabilities of the semiparametric approach in approximating those trends were clearly demonstrated. Traditionally, we would have used polynomial models to approximate the behaviors. However, as our example has shown, sometimes even higher order polynomials may not be able to approximate the trends successfully. Further, failure to approximate the temporal trends closely may also lead to incorrect conclusions concerning the effects of thinning on microclimates, as in the case of ST. The semiparametric smoothing splines, on the other hand, not only closely tracked the temporal response trends, but also correctly detected the effects of different thinning intensities on ST. Our example has also shown that we can reveal the temporal trends embedded in the monitoring data with proper parametric models, as in the case of ATR and SWP. However, it did take considerably more effort to develop appropriate parametric models for these two variables.

Information revealed using the proposed approach would provide valuable insights into the effects of thinning on other relevant ecological processes. For instance, in our example, the results suggested that although all the thinned stands had a higher ATR initially, the thinning effect declined quickly, especially in the strongly thinned stand. Since the canopies of the thinned stands had not recovered quickly enough to account for the downward trend, it is likely that other factors were modulating ATR within the thinned stands. Another instance was the trends of SWP over the 2-year period. During the first summer (wet season) after thinning, the SWPs for the four treatments were about the same. However, during the second summer after thinning, owing to the severe drought, the SWPs of the strongly and moderately thinned stands were higher than that of the control. This could have important implications for soil nutrient dynamics (Thibodeau et al. 2000). An ANOVA-only approach is unlikely to provide such insights.

Like that of least-squares regression, the performance of smoothing splines can be significantly affected by high-leverage data points (e.g., outliers) (Simonoff 1996). They can affect the estimation of an appropriate smoothing parameter, since a smoothing spline, like any approximation method, must account for the presence of those points. For monitoring data, however, it would be difficult to determine whether a set of points are true outliers (as a result of sensor errors, for example) or legitimate observations from a process with a large variance. We can see the effects of variances on the performance of smoothing splines in our example. Each of the two monthly average temperature variables had a small variance, and the models performed well. The monthly average ATR, on the other hand, showed large variations both within and between treatments, especially in the strongly thinned stand. Even after the heterogeneity in the variances was successfully accounted for, the fit was not as good as we would hope. For SWP, it was not just the variances that were affecting model performance. Rapid variations in SWP also contributed to the not-so-satisfactory performance of the semiparametric smoothing spline models.

The proposed approach can be viewed as an extension of the generalized additive models of Hastie and Tibshirani

### Table 1. Model fitting and performance for the fitted semiparametric smoothing spline and linear models.

<table>
<thead>
<tr>
<th>Variable a</th>
<th>Modelb</th>
<th>$\lambda$</th>
<th>dfc</th>
<th>$\sigma_\varepsilon$</th>
<th>AIC d</th>
<th>BIC e</th>
<th>Log-likelihood value</th>
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</thead>
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<td>AT</td>
<td>SSS</td>
<td>$1.23 \times 10^{-9}$</td>
<td>7</td>
<td>0.13</td>
<td>411.05</td>
<td>438.25</td>
<td>–198.52</td>
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<td></td>
<td>12</td>
<td>4.94</td>
<td>598.47</td>
<td>644.91</td>
<td>–287.24</td>
</tr>
<tr>
<td>ST</td>
<td>SSS</td>
<td>$2.92 \times 10^{-8}$</td>
<td>7</td>
<td>0.88</td>
<td>1009.22</td>
<td>1036.37</td>
<td>–497.61</td>
</tr>
<tr>
<td>Parametric</td>
<td></td>
<td></td>
<td>11</td>
<td>2.05</td>
<td>1124.95</td>
<td>1167.45</td>
<td>–551.48</td>
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<tr>
<td>ATR</td>
<td>SSS</td>
<td>$9.03 \times 10^{-8}$</td>
<td>15</td>
<td>0.08</td>
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<td>1205.30</td>
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<td></td>
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<td>0.10</td>
<td>1163.55</td>
<td>1221.67</td>
<td>–566.77</td>
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<tr>
<td>SWP</td>
<td>SSS</td>
<td>$6.03 \times 10^{-9}$</td>
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<td>2.19</td>
<td>2882.30</td>
<td>2925.20</td>
<td>–1430.15</td>
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<tr>
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<td></td>
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<td>1.75</td>
<td>2904.92</td>
<td>2955.61</td>
<td>–1439.46</td>
</tr>
</tbody>
</table>

Note: For the features of each model see the text. $\lambda$ is the estimated smoothing parameter and $\sigma_\varepsilon$ is the estimated error standard deviation.

aAT, air temperature; ST, soil temperature; ATR, air-temperature range; SWP, soil water potential.
bSSS is the semiparametric smoothing spline model and “parametric” is the parametric linear model.
cNumber of parameters in the model.
dAkaike’s information criterion; for this criterion, a model with a smaller value is preferred.
eBayesian information criterion; as with AIC, a model with a smaller value is preferred.
(1986, 1990). Generalized additive models are also flexible and available in many statistical packages. The generalized additive mixed-model function (gam) of R package mgcv (Wood 2004, 2005) can handle both mixed effects and correlations. The proposed approach could also be implemented using the gam function. However, in terms of smoothing spline capabilities, mgcv is currently not as versatile as the package used in this study.

Nowadays, monitoring various aspects of biodiversity (e.g., number of species, abundance of species, or the presence/absence of certain species) is an integral part of many thinning experiments (Wetzel and Burgess 2001; Hagar et al. 2004; Harrison et al. 2005). Since the proposed approach can handle various data types via a suitable link function (e.g., logit, Poisson), it can be used to analyze those types of monitoring data as well.

In exploratory data analysis, we typically apply smoothing procedures (e.g., loess or smoothing spline) to help us to detect interesting and unusual features. Traditionally, we would subsequently attempt to construct suitable parametric models suggested by the smoothed results. The proposed approach allows us to use the smoothed results directly to test relevant hypotheses. We should emphasize that we are not recommending that only smoothing methods be used to analyze monitoring data. Parametric modeling still has important roles in analyzing monitoring data, as in our example. Rather, our purpose is to show that by incorporating smoothing splines (or other nonparametric regression methods) directly into data analysis, we can simultaneously achieve the two objectives of monitoring microclimates: to detect the effects of thinning on, and reveal the temporal response trends of, microclimatic variables. Our ability to determine how thinning affects other ecological processes will be hampered if only one of these objectives is achieved.

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