Comparison of different stomatal conductance algorithms for ozone flux modelling


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1 Introduction

The ozone deposition model (DO3SE) that has been developed and applied within the EMEP photo-oxidant model (Emerson et al., 2000, Simpson et al. 2003) currently estimates stomatal ozone flux using a stomatal conductance (gs) model based on the multiplicative algorithm initially developed by Jarvis (1976). This model links gs to environmental and phenological parameters with a set of response functions. However, there exist a number of alternative and well established methods to calculate gs, with the photosynthesis-based algorithm becoming increasingly more popular in situations where carbon-energy flux modelling is required at the regional or global scale. This algorithm uses a semi-mechanistic approach based primarily on the close relationship between gs and net photosynthetic rate, which provides the link between gas (e.g. H2O, O3) influx and the prevailing climatic conditions (Ball et al., 1987); here we use the photosynthesis-based algorithm implemented in the generic leaf-level photosynthesis model LEAFC3 developed by Nikolov et al. (1995).

In order to find the most appropriate algorithm for use in DO3SE, both gs modelling approaches have been evaluated focusing on i) the model (input) requirements and ii) the performance of the models in predicting gs using site-specific data. The models were parameterised for two crop (grapevine and wheat) and two tree (birch and beech) species and have been applied to various datasets covering different European regions (North, Central and South Europe). Ultimately, the performance of the models in predicting total ozone deposition to vegetated surfaces at a regional scale will be tested, similar to comparisons described for grapevine in Emberson et al. (this volume).

2 Parameterisation of the models

The multiplicative gs algorithm used in DO3SE is given by equation [1] as described in Emberson et al. (2000).

\[ g_{sto} = g_{max} \times f_{phen} \times f_{PFD} \times \max\{f_{min}, (f_{air} \times f_{PFD} \times f_{SWP})\} \]

where \( g_{sto} \) is the actual gs and \( g_{max} \) is the maximum gs occurring during the growing season. The factors
functions representing the relationships between species included in this analysis, i.e. grapevine (Vitis vinifera) and birch (Betula pendula). Definitions of the functions representing the relationships between g\textsubscript{s} and environmental and phenological parameters can be found in Emberson et al. (2000).

Table 2 shows the main input parameters required by LEAFC3 and its parameterisation for grapevine and birch. The values for V\textsubscript{m25} (maximum rate of carboxylation at 25 °C) and J\textsubscript{m25} (maximum rate of potential electron transport at 25 °C) have been derived from a comprehensive literature review. The temperature response functions for the parameters J\textsubscript{m25}, K\textsubscript{25}, K\textsubscript{25} and \( \delta \) (CO\textsubscript{2} compensation point in the absence of mitochondrial respiration) were taken from a recently published revision of LEAFC3 by Müller et al. (2005), whereas the temperature response function for V\textsubscript{m25} remained the same as in Nikolov et al. (1995).

Since the primary aim of this paper is to compare the predictive abilities of the two g\textsubscript{s} algorithms, both models were parameterised for local conditions (see Tables 1 and 2). This is to ensure that model comparisons are affected as little as possible by difficulties associated with establishing parameterisation of model functions (e.g. see Emberson et al. this volume). However, it should be noted that local parameterisa-
Table 2: Main input parameters required for LEAFC3 and parameterisation for grapevine and birch; $V_{m_{25}}$ = maximum rate of carboxylation at 25 °C, $J_{m_{25}}$ = maximum rate of potential electron transport at 25 °C, $K_{c_{25}}$ and $K_{o_{25}}$ = Michaelis-Menten constant of Rubisco for carboxylation and oxygenation at 25 °C respectively, $m$ = species-specific "composite sensitivity" of $g_5$ to $A_n$, $Mm$ soil moisture multiplier [0,1]. Values in brackets represent the range of $V_{m_{25}}$ and $J_{m_{25}}$ derived from a comprehensive literature review.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Grapevine</th>
<th>Birch</th>
<th>Units</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>$V_{m_{25}}$</td>
<td>70 (60-100)</td>
<td>60 (28-169)</td>
<td>μmol m⁻² s⁻¹</td>
<td>Büker et al. (in prep)</td>
</tr>
<tr>
<td>$J_{m_{25}}$</td>
<td>140 (120-260)</td>
<td>120 (80-230)</td>
<td>μmol m⁻² s⁻¹</td>
<td>Büker et al. (in prep)</td>
</tr>
<tr>
<td>$K_{c_{25}}$</td>
<td>404.09</td>
<td>404.09</td>
<td>μmol mol⁻¹</td>
<td>cf. Müller et al. (2005)</td>
</tr>
<tr>
<td>$K_{o_{25}}$</td>
<td>278.40</td>
<td>278.40</td>
<td>mmol mol⁻¹</td>
<td>cf. Müller et al. (2005)</td>
</tr>
<tr>
<td>$m$</td>
<td>8.0</td>
<td>9.0</td>
<td>-</td>
<td>cf. Nikolov et al. (1995)</td>
</tr>
<tr>
<td>$g_{min}$</td>
<td>0.05</td>
<td>0.03</td>
<td>mol m⁻² s⁻¹</td>
<td>obtained from $g_5$ in dark</td>
</tr>
<tr>
<td>$Mm$</td>
<td>-</td>
<td>-</td>
<td>fraction</td>
<td>not used so far</td>
</tr>
</tbody>
</table>

...to the local values (Table 1 and 2) and discussed in relation to the results presented in this study.

3 Description of datasets

Four European datasets have been identified to evaluate $g_5$ using the algorithms described above: i) a Mediterranean grapevine dataset from Spain (Jacobs, 1996), ii) a boreal birch dataset from Finland (Oksanen, 2003), iii) a temperate beech dataset from...

Table 3: Origin of datasets and range of main meteorological, physiological and phenological parameters for grapevine, birch, beech and wheat (value in brackets indicates mean).

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Grapevine</th>
<th>Birch</th>
<th>Beech</th>
<th>Wheat</th>
<th>Units</th>
</tr>
</thead>
<tbody>
<tr>
<td>Location</td>
<td>Tomelloso, E</td>
<td>Kuopio, FIN</td>
<td>Lattecaldo, CH</td>
<td>Alcalá de Henares, E</td>
<td>-</td>
</tr>
<tr>
<td>Temperature</td>
<td>13.1 - 40.0 (28.4)</td>
<td>14.8 - 23.6 (20.0)</td>
<td>21.2 - 31.7 (26.8)</td>
<td>13.8 - 43.2 (28.2)</td>
<td>°C</td>
</tr>
<tr>
<td>VPD</td>
<td>0.5 - 5.9 (2.7)</td>
<td>0.1 - 1.6 (1.0)</td>
<td>1.0 - 2.8 (1.8)</td>
<td>0.2 - 7.3 (2.3)</td>
<td>kPa</td>
</tr>
<tr>
<td>PPFD</td>
<td>2.0 - 2133.0 (784.6)</td>
<td>10.0 - 1870.0 (762.8)</td>
<td>1500.0 (constant)</td>
<td>7.6 - 2349.7 (641.9)</td>
<td>μmol m⁻² s⁻¹</td>
</tr>
<tr>
<td>$g_5$</td>
<td>1.7 - 251.3 (97.8)</td>
<td>13.5 - 450.6 (181.1)</td>
<td>22.4 - 714.0 (216.9)</td>
<td>14.0 - 681.2 (184.7)</td>
<td>mmol H₂O</td>
</tr>
<tr>
<td>$A_n$</td>
<td>-0.2 - 20.7 (7.9)</td>
<td>-</td>
<td>1.9 - 15.2 (9.1)</td>
<td>-2.7 - 56.7 (12.2)</td>
<td>μmol CO₂ m⁻² s⁻¹</td>
</tr>
<tr>
<td>Measuring period</td>
<td>17/6 - 28/6</td>
<td>18/6 - 1/8</td>
<td>11/5 - 4/10</td>
<td>19/4 - 12/6</td>
<td>-</td>
</tr>
<tr>
<td>(no. of measuring days)</td>
<td>(7)</td>
<td>(11)</td>
<td>(9)</td>
<td>(18)</td>
<td>-</td>
</tr>
<tr>
<td>$n$</td>
<td>615</td>
<td>1246</td>
<td>272</td>
<td>668</td>
<td>-</td>
</tr>
</tbody>
</table>
Switzerland (Novak, pers. comm.) and iv) a Mediterranean wheat dataset from Spain (De la Torre, 2004). In addition, two further datasets for boreal Scots pine and Mediterranean wheat from Finland (Tuovinen et al., 2000) and Italy (Gerosa et al., 2003) respectively have been acquired. These two datasets contain O₃ deposition data which qualifies them for a comparison of the performance of the different gₛ algorithms when used in the DO₃SE model for total ozone deposition modelling.

Table 3 describes the four datasets, listing the range of the main meteorological, physiological and phenological variables. The model runs were performed using both minute-by-minute (i.e. initial time steps of measurements) and hourly mean input data. The conversion to hourly means is intended to ensure that gₛ measurements reflect the prevailing meteorological conditions since it is acknowledged that changes in gₛ will often lag behind changes in environmental variables. The resulting gₛ-data were pooled to gain diurnal and seasonal courses of gₛ to test the algorithm's ability to account for phenomena such as gₛ midday depression and autumnal senescence. Due to limited space, only results for grapevine and birch will be presented in the following.

A common problem with all datasets was the lack of information describing soil water status, a variable necessary as input to both gₛ models. As such, it has been necessary to assume that water availability was not limiting to gₛ over all observation periods. This assumption is discussed in relation to the results.

4 Performance of algorithms

Exemplary for all four datasets, Figure 1 shows the capacity of the multiplicative and photosynthesis-based algorithm in predicting gₛ using minute-by-minute input data. Both algorithms tend to overestimate gₛ (slopes of the linear regressions are 0.57 and 0.64 for multiplicative and photosynthesis based models, respectively). The models are able to account for only 40% (multiplicative) and 32% (photosynthesis-based model) of the variation in the datasets as denoted by the respective R²-values. As such, these data would suggest that the multiplicative model performs marginally better than the photosynthesis-based model though neither model could be considered to be performing well.

Diurnal courses for grapevine using hourly means averaged over the course of the measuring campaign (7 days in June 1991) are shown in Figure 2; analysis of these pooled data result in both algorithms providing a much better relationship between observed and modelled gₛ. This would indicate that both models can effectively predict diurnal
trends. Both models give a good correspondence between observed and modelled \( g_s \) for the morning hours (6:00 to 11:00); over the course of the afternoon however, the predictions diverge from the actual mean values and are not able to re-produce the variations in \( g_s \). In fact, the multiplicative algorithm shows shifted peaks after noon whereas the photosynthesis-based algorithm tends to produce a more constant decline in \( g_s \). However, both models are able to predict the observed midday depression of \( g_s \) and its decline in the later afternoon.

The birch dataset was selected to show the ability of the algorithms to predict seasonal changes in \( g_s \) since this was the dataset recorded over a longer period during the growing season. Figure 3 gives an indication of the seasonal variability of \( g_s \) as predicted by both algorithms in comparison with the observed course of \( g_s \). The charts represent the \( g_s \) average for the two hours between 11:00 a.m. and 1:00 p.m. for which the models performed well (Figure 2). Although the seasonal period only represents conditions at the height of the growing season (i.e. effects of senescence haven’t been observed during the measuring campaign for birch), the graphs show the general ability of the algorithms to predict changes in \( g_s \) over longer time periods. In general, both models tend to overestimate \( g_s \).

5 Discussion and outlook

Both algorithms showed a similar performance in predicting \( g_s \) for time-steps of various lengths (minute-by-minute, daily and seasonal), with the multiplicative algorithm yielding slightly higher \( R^2 \)-values for the relationship between observed and modelled \( g_s \). The photosynthesis-based algorithm used in LEAF3 requires more detailed meteorological (e.g. ambient \( CO_2 \)-concentration, dew-point temperature) input data and plant-physiological (e.g.
V_{m\text{25}}, J_{m\text{25}}) parameters. Since the latter are often not available, a site-specific parameterisation accounting for differences in g_s due to plants growing under different climatic conditions is not easy to achieve for this algorithm, i.e. might only be possible via a literature review. Furthermore, the obvious variance (Figure 1) of g_s when using the photosynthesis-based algorithm might be at least partly attributed to the questionable assumption that the g_s is always closely coupled with A_n. Figure 4 shows the variation in the coupling of g_s and A_n over the course of the growing season as observed for beech.

In contrast, the relative weakness of the multiplicative algorithm resulting in similar variances as seen for the photosynthesis-based algorithm lies in its dependence on g_{\text{max}} which is difficult to derive from published literature (see Emberson et al. this volume) and may well vary within species according to prevailing climatic conditions.

For the photosynthesis based algorithm a revised soil moisture deficit function has been published recently (Nikolov & Zeller, 2003), which will be assessed in the near future. However, the soil drought effect for the grapevine and birch dataset was assumed to have been low, because of very deep roots well below the groundwater level for grapevine (Jacobs, pers. comm.) and the low VPD values observed for birch.

The performance of the algorithms in predicting total ozone deposition to vegetated surfaces at a regional scale using the DO_{3SE} model will be tested using the above described Scots pine and wheat dataset. This will provide further information on how different g_s algorithms compare when used for estimating total O_3 deposition and how the generic DO_{3SE} parameterisation is able to represent individual species at site-specific locations.

### References


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