Aggregating spatial heterogeneity in a bush vegetation patch in semi-arid SE Spain: A multi-layer model versus a single-layer model

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Summary In semi-arid areas, where vegetation is sparse and clumped, models used to estimate evapotranspiration ($\lambda E$) consider soil and plants as different sources of evaporation. When working at higher scales of heterogeneity, the modelling of surface fluxes introduces effective parameters that enclose the sub-grid heterogeneity. In this work we used both approaches to estimate the $\lambda E$ of a sparse-vegetation patch of Retama sphaerocarpa (L.) Boiss in a semi-arid area in southeast Spain. Firstly, we used a multi-layer model considering plant, soil under plant and bare soil, each with its own surface and aerodynamic resistances and available energy, interacting at a within canopy height. Secondly, we used a single-layer model that uses the effective surface and aerodynamic resistances of the patch, calculated by different aggregations of the soil and plant resistances considered in the multi-layer model. The estimates of $\lambda E$ were compared with measured values obtained by an Eddy covariance system. Results show that the use of effective surface resistances aggregated in parallel and effective aerodynamic resistances aggregated in series in a single-layer model produced similar estimates of $\lambda E$ as a multi-layer model. When compared to the measured values, the estimates of the single-layer model were even more accurate than the estimates of the multi-layer model. The results of this paper show that, in areas with low vegetation cover, a simple model, where patch-scale heterogeneity is
Introduction

The spatial heterogeneity of an area is important when modelling surface energy fluxes for hydrological or meteorological purposes. It is particularly important to understand how the heterogeneity at the sub-grid scale can be considered when modelling the surface fluxes in meso-scale models or GCs (Blyth, 1995; Noilhan et al., 1997). Particularly the latent heat flux, or evapotranspiration ($\dot{E}$), depends strongly on the heterogeneity of the landscape, which makes it necessary to know the scale of heterogeneity that we are actually facing when modelling $\dot{E}$ (Blyth et al., 1993; Huntingford et al., 1995; Dolman and Blyth, 1997).

Many models for estimating $\dot{E}$ are based on the Penman–Monteith model (Monteith, 1965). This model considers that water vapour flows through a gradient of water vapour concentration, between stomata and air, being controlled by a surface and an aerodynamic resistance. This model assumes that canopies can be regarded as a single, uniform and homogeneous surface (also known as "big-leaf"), regarded as the only source of evapotranspiration. Therefore, for sparse-vegetation areas, where heterogeneity is introduced by the presence of patches of vegetation separated by open spaces, this model is not appropriate. In these sparse-vegetation areas, heterogeneity comes from the roughness elements, normally represented by plants, and it is assumed that the distance between plants is of the same order of magnitude as the height of the vegetation. This scale of heterogeneity is often named as patch-scale heterogeneity, the single-source Penman–Monteith model was extended to account soil and plant as different evaporating sources. One of the approaches used was the multi-layer approach (Huntingford et al., 1995), which assumes that each of the evaporating sources is linked via a resistance network where temperature and water vapour pressure deficit within the canopy are modified by the interaction of the different sources. Therefore, models built under this approach, often called sparse-vegetation models (Blyth, 1995), calculate the total evapotranspiration as the sum of the Penman–Monteith equations of each source, weighted by their fractional covers, plus a set of coefficients that represent the combination of the surface and aerodynamic resistances. Apart from the surface and aerodynamic resistances of each source, these models also take into account an aerodynamic resistance between the height where the different sources interact, also called the mean canopy source height ($z_m$) and the reference height above the vegetation ($z_r$). Examples of these multi-layer models can be found elsewhere (Shuttleworth and Wallace, 1985; Dolman, 1993; Domingo et al., 1999; Verhoef and Allen, 2000).

Another approach to account for the heterogeneity of a surface involves the use of effective parameters (Fiedler and Panofsky, 1976). Effective parameters can be defined as those parameters that give rise to the same flux as if that flux was calculated from individual patch contributions, each with their own parameter (Dolman and Blyth, 1997). This approach has been mainly used when modelling evapotranspiration at a higher scale of heterogeneity, when the scale of heterogeneity due to the roughness elements is considered to be homogeneous. These scales of heterogeneity are often called micro or meso-scale heterogeneity (Mahrt, 2000). However, in this paper we will consider the use of effective parameters when modelling evapotranspiration at patch-scale heterogeneity. We will calculate the effective surface and aerodynamic resistances of the patch through the aggregation of the component resistances considered in the multi-layer model. These effective surface and aerodynamic resistances are introduced into a Penman–Monteith type equation to calculate the total evapotranspiration of the patch. This approach takes into account the different sources of the patch and therefore the patch-scale heterogeneity through the effective resistances, though it considers all variables and parameters at $z_r$, not considering the interaction of the sources at $z_m$. Therefore in this paper we will refer to this approach as the single-layer model. It should be noticed that unlike the effective resistances used in the single-layer model, the resistances used in the Penman–Monteith original model did not depict the heterogeneity of the patch.

Thus, the aim of this work is to compare two approaches for confronting patch-scale heterogeneity when modelling $\dot{E}$. On one hand, a multi-layer approach, using a sparse-vegetation model where heterogeneity is accounted for by aggregating the partial $\dot{E}$ of each source and assuming that all sources interact at a given height. On the other hand, a single-layer approach, where the heterogeneity of the whole patch is accounted for by means of the effective resistances, by aggregating the surface and aerodynamic resistances of the different sources, and by using a simple equation that does not consider any interaction between these sources. To calculate these effective resistances different methods of aggregation of the source resistances were tested. The estimated values of $\dot{E}$ obtained with both models were compared with values measured with an Eddy covariance system.

Theory

The multi-layer model (ML)

The multi-layer model used in this work, named hereafter as ML model, is a parameterisation of the sparse-vegetation evapotranspiration model developed by Domingo et al. (1999). This model is a three-layer model that considers three sources of $\dot{E}$, namely plant (p), soil under plant (s) and bare soil (bs). This model has been previously parameterised and validated for three different bush vegetation patches in southeastern semi-arid Spain (Villagarcia, 2000).
Nomenclature

Latin alphabet

\(a\) constant that relates \(r_i^a\) with \(u_h\) (0.0143 in this analysis)

\(A, A_i\) total available energy for the whole patch and for each \(i\) source, respectively (W m\(^{-2}\))

\(b_d\) parameter indicating how \(g_i^d\) changes with \(D_r\) (mol m\(^{-2}\) s\(^{-1}\) kPa\(^{-1}\))

\(b_\ell\) coefficient of linearity between the measured and estimated values of \(g_i^\ell\) (umol m\(^{-2}\) s\(^{-1}\))

\(c_\ell\) specific heat of air (J kg\(^{-1}\) K\(^{-1}\))

\(C_j\) coefficients that represent the combination of the resistances considered for each \(i\) source, in the ML model

\(d\) Displacement height (m)

\(D_r\) water vapour pressure deficit at \(z_r\) (kPa)

\(e_r\) water vapour pressure at \(z_r\) (kPa)

\(f\) fraction cover of vegetation

\(g_i^d\) leaf conductance (mol m\(^{-2}\) s\(^{-1}\))

\(g_i^m\) maximum \(g_i^d\) at light saturation (mol m\(^{-2}\) s\(^{-1}\))

\(g_i^\ell\) maximum \(g_i^d\) at light saturation and water vapour saturation of air (mol m\(^{-2}\) s\(^{-1}\))

\(g_i^e\) plant conductance (mol m\(^{-2}\) s\(^{-1}\))

\(G_i\) soil heat flux for each source (W m\(^{-2}\))

\(h\) average height of vegetation (m)

\(H\) sensible heat flux (W m\(^{-2}\))

\(L\) patch leaf area index (m\(^2\) m\(^{-2}\))

\(L_p\) plant leaf area index (m\(^2\) m\(^{-2}\))

\(n\) coefficient indicating the decrease in the turbulent diffusion through the vegetation (2.5 in this analysis)

\(P_{Mi}\) Penman–Monteith type equations for each \(i\) source (p, s and bs) (W m\(^{-2}\))

\(Q\) flux of photosynthetically active radiation (mol s\(^{-1}\))

\(r_i^a\) aerodynamic resistance between \(z_m\) and \(z_r\) (s m\(^{-1}\))

\(r_i^s, r_i^b, r_i^m, r_i^\ell, r_i^e\) aerodynamic resistances of the plant, soil under plant and bare soil, respectively (s m\(^{-1}\))

\(r_i^s, r_i^b, r_i^m, r_i^\ell, r_i^e\) surface resistances of the plant, soil under plant and bare soil, respectively (s m\(^{-1}\))

\(r_i^a\) average aerodynamic leaf resistance of the canopy leaves (s m\(^{-1}\))

\(r_i^s, r_i^b\) aerodynamic and surface resistances, respectively, for each \(i\) source (s m\(^{-1}\))

\(r_i^s, r_i^b\) effective aerodynamic and surface resistances, respectively, for the whole source (s m\(^{-1}\))

\(r_i^a\) effective aerodynamic and surface aggregated resistances, respectively, of the patch (s m\(^{-1}\))

\(r_i^s, r_i^b\) effective aerodynamic and surface resistances, respectively, aggregated in parallel (s m\(^{-1}\))

\(R_{i,n}\) combination of the resistances for each \(i\) source and for \(r_i^a\), respectively, used in the ML model

\(R_{i,n}\) net radiation for each \(i\) source (W m\(^{-2}\))

\(T_r\) air temperature at \(z_r\) (°C)

\(T_0\) air temperature at \(z_0\) (°C)

\(u_h\) wind speed at average canopy height (m s\(^{-1}\))

\(u_c\) wind speed at \(z_r\) (m s\(^{-1}\))

\(u_f\) friction velocity (m s\(^{-1}\))

\(w\) average width of the leaves (m)

\(z_m\) mean canopy source height, where the different sources interact (m)

\(z_r\) reference height above the soil, where meteorological variables are measured (m)

\(z_0\) roughness length (m)

Greek alphabet

\(\gamma\) psychrometric constant (Pa K\(^{-1}\))

\((1 + \delta)'\) stability correction factor

\(\Delta\) slope of the curve relating water vapour pressure of saturated air with temperature (Pa °C\(^{-1}\))

\(\theta\), \(\theta_4\), \(\theta_{bs}\) soil water content (m\(^3\) m\(^{-3}\))

\(\kappa\) coefficient of the light extinction of the canopy

\(iE\) evapotranspiration or latent heat flux (W m\(^{-2}\))

\(\iota E_{ML}\) total evapotranspiration calculated with the ML model (W m\(^{-2}\))

\(\iota E_{SL}\) total evapotranspiration calculated with the SL model (W m\(^{-2}\))

The model takes into account the surface and aerodynamic resistances of each source, \(r_i^s, r_i^b, r_i^m, r_i^\ell, r_i^e\), where subscripts \(s, b, m, \ell, e\) refer to surface and aerodynamic resistances respectively, and it assumes that the different sources interact at a height \(z_m\) (\(z_0 + d\)), considering another aerodynamic resistance (\(r_i^a\)) between this height and the reference height (\(z_r\)), as it is shown in Fig. 1a.

Because the ML model considers that all sources interact at \(z_m\), the total evapotranspiration \(\iota E_{ML}\) cannot be calculated solely as the sum of the partial \(\iota E\) of each source. Therefore, \(\iota E_{ML}\) is calculated as the sum of the Penman–Monteith equations of each source, weighted by their fractional covers (\(a_i\)), plus a set of coefficients that represent the combination of the resistances considered:

\[
\iota E_{ML} = \sum_i a_i C_{PM_i}
\]  

where \(i = s, b, m, \ell, e\) and \(PM_i\) are Penman–Monteith type equations for each source given by:

\[
PM_i = \frac{\Delta A_i r_i^e + \rho C_p D_i + \Delta A r_i^a}{(\Delta + \gamma)(r_i^s + r_i^b) + \gamma r_i^a}
\]  

where \(A_i, r_i^s\) and \(r_i^b\) are the available energy, and the aerodynamic and surface resistances respectively, for each
source $i$; $\Delta$ is the available energy for the whole surface; $\rho$ is the air density; $C_p$ is the specific heat of air; $\Delta$ is the slope of the curve relating water vapour pressure of saturated air with temperature; $\gamma$ is the psychrometric constant; and $D_r$ is the water vapour pressure deficit at $z_t$. The available energy $A$ is the available energy calculated as $R_{n,i} - G_i$ (net radiation minus soil heat flux), for each source $i$. To estimate $R_{n,i}$ an energy partition sub-model was included in the ML model (Domingo et al., 2000). This sub-model needs another iteration to calculate the temperature of air at $z_m$ ($T_m$), because this variable depends on sensible heat ($H$), calculated as $A - \dot{E}_{ML}$. Domingo et al. (2000) obtained no significant differences between the $R_{n,i}$ measured and calculated with the sub-model, in a vegetation patch similar to the one used in this work. $G_i$ is calculated from $R_{n,i}$ (see "Materials and methods").

$C_i$ in Eq. (1) are the equations combining the different resistances, calculated as:

$$C_p = \frac{R_{p}R_{so}(R_{so} + R_{s})}{R_{p}R_{so} + f R_{p}R_{so}R_{s} + fR_{p}R_{so}R_{s} + (1-f)R_{p}R_{so}R_{s}} \quad (3)$$

$$C_s = \frac{R_{p}R_{so}(R_{so} + R_{s})}{R_{p}R_{so} + f R_{p}R_{so}R_{s} + fR_{p}R_{so}R_{s} + (1-f)R_{p}R_{so}R_{s}} \quad (4)$$

$$C_{so} = \frac{R_{p}R_{so}(R_{so} + R_{s})}{R_{p}R_{so} + f R_{p}R_{so}R_{s} + fR_{p}R_{so}R_{s} + (1-f)R_{p}R_{so}R_{s}} \quad (5)$$

where:

$$R_i = (\Delta + \gamma) R^A + \gamma R^S \quad (6)$$

$$R_s = (\Delta + \gamma) R^A \quad (7)$$

$f$ and $(1 - f)$ correspond to the fraction covers of vegetation and bare soil, respectively.

With this ML model we need to parameterise semi-empirical equations (see "Materials and methods") that relate the different surface and aerodynamic resistances, as well as the available energy, with the input micrometeorological variables, which are: net radiation ($R_n$), wind speed, water vapour pressure of air and temperature of air at reference height ($u_*, e_*$, and $T_a$, respectively), and soil moisture of soil under plant and bare soil ($\theta_s$ and $\theta_{so}$, respectively).

The single-layer model (SL)

The single-layer model used in this work to estimate the total $\dot{E}$ of the patch, hereafter referred to as the SL model, is a Penman–Monteith equation where all the parameters and variables are considered at reference height, and the two resistances of the equation are the effective aerodynamic ($r^A$) and surface ($r^S$) resistances for the whole surface (Fig. 1b). Accordingly, the SL model equation is as follows:

$$\dot{E}_{SL} = \frac{\Delta \Delta + \nu C_p D_s / r^S}{\Delta + \gamma (1 + r^A / r^S)} \quad (8)$$

where $\dot{E}_{SL}$ is the total $\dot{E}$ estimated with this SL model.

Calculation of the effective resistances ($r^A$)

Many authors have calculated the $r^A$ at a given scale by aggregating the resistances at the smaller scale (Blyth et al., 1993; Chehbouni et al., 1993; Chehbouni et al., 2000; Dolman, 1992; Dolman and Blyth, 1997; McNaughton, 1994; Shuttleworth, 1997). In this work, we aggregate the soil and plant resistances calculated for the ML model in order to obtain the aggregated $r^A$ of the patch ($\langle r^A \rangle$).

Blyth et al. (1993) indicate that the recommended aggregation varies with the flux and the type of resistance, pointing out that in heterogeneous terrain the effective resistances should be an average of the resistances at the smaller scale, weighted by the flux. This has the inconvenience of needing to know the fluxes before calculating the effective resistances. Therefore, to avoid the need of previous knowledge of the fluxes, an approximation to calculate ($r^A$) can be obtained by aggregating the resistances in parallel or in series, following Ohm’s law (Blyth et al., 1993; Dolman and Blyth, 1997; Noilhan et al., 1997).

Blyth et al. (1993), in referring to the work of other authors (Mason, 1988; Wood and Mason, 1991), indicate that for momentum, resistances are set in parallel, while for heat they are set in series. In the case of $\dot{E}$, Blyth et al. (1993) propose a practical way of aggregating the resistances by averaging the resistances aggregated in parallel and in series.

These approximations are proposed for meso-scale and GCM models, but at patch-scale, where the aggregation is
between soil and plant resistances, it is not clear what kind of aggregation should be used. Though it is clear that the surface and aerodynamic resistances of a source are in series (Jones, 1992), it is not clear how the resistances of soil and plant are related to each other. Therefore, in this paper we have used different kinds of aggregation for the surface and aerodynamic resistances of the patch used in the ML model.

According to the resistances network shown in Fig. 1a, surface resistances of soil and plant seem to be set in parallel. Therefore, to calculate the effective surface resistance of the patch ($r_{s,p}^e$) we aggregated soil and plant resistances in parallel, weighted by the fraction cover of the vegetation of the patch ($f$), as follows:

$$
\frac{1}{r_{s,p}^e} = f \left( \frac{1}{r_s^a} + \frac{1}{r_s^b} + (1 - f) \left( \frac{1}{r_p^e} \right) \right)
$$

where $r_{s,p}^e$ is the effective surface resistance aggregated in parallel.

However, we have also tested the aggregation proposed by Blyth et al. (1993), by averaging the effective surface resistances aggregated in parallel and in series, given by:

$$
\frac{1}{r_s^e} = \frac{1}{2} \left( \frac{r_s^a + 1/\left( \frac{1}{r_p^e} \right)}{r_s^b} \right)
$$

where $r_s^e$ is the averaged effective surface aggregated resistance and $r_s^a$ is the effective surface resistance aggregated in series, given by:

$$
\frac{1}{r_s^a} = f \left( \frac{1}{r_s^b} + \frac{1}{r_p^e} + (1 - f) \left( \frac{1}{r_p^e} \right) \right)
$$

To calculate the effective aerodynamic aggregated resistance ($r_s^e$), in this paper we tested the three aggregation schemes, weighted by $f$, given by:

$$
\frac{1}{r_s^e} = \frac{1}{2} \left( \frac{r_s^a + 1/\left( \frac{1}{r_p^e} \right)}{r_s^b} \right) + r_s^a
$$

$$
\frac{1}{r_s^a} = f \left( \frac{1}{r_s^b} + r_s^a + (1 - f) r_s^b \left( \frac{1}{r_p^e} \right) \right)
$$

$$
\frac{1}{r_s^b} = \frac{1}{2} \left( \frac{1}{r_s^a} + r_s^b \right)
$$

where $r_s^a$ and $r_s^b$ are the effective aerodynamic resistances aggregated in parallel, and in series, respectively, and $r_s^e$ is the averaged effective aerodynamic aggregated resistance. To calculate $r_s^e$, the atmospheric aerodynamic resistance ($r_a^e$) is always aggregated in series, as this is its position relative to the soil and plant aerodynamic resistances (Fig. 1b).

To estimate $\Delta E_{sl}$ we combined the different effective surface and aerodynamic aggregated resistances.

Materials and methods

Field experiments for measuring plant and soil resistances, and measurements of the different micro-meteorological variables, as well as of $\Delta E$, were carried out in a sparse-vegetation patch with *Retama sphaerocarpa* (L.) Boiss. shrubs, characteristic of the semi-arid southeastern Spain.

Site description

The selected patch was located in the Rambla Honda field site, a dry valley near Tabernas, Almería, Spain (37°8’N, 2°22’W). This field site has previously been described in detail by Puigdefábregas et al. (1996). The valley has been abandoned for several decades, and currently has little agricultural activity apart from small-scale sheep herding. Vegetation is dominated by three perennial species, *R. sphaerocarpa* shrubs on the valley floor, *Stipa tenacissima* L. tussocks on steep valley walls and *Anthyllis cytisoides* L. shrubs on alluvial fans between the two of them. The valley bottom has deep loamy soils that overlay mica schist bedrock. The field site is located at 630 m a.s.l. with an average annual rainfall of 220 mm, average mean temperature of 16 °C and a dry season from around June to September.

The patch selected is located at the bottom valley, with vegetation dominated by plants of *R. sphaerocarpa* placed in a sparse way, where plants are separated by bare areas dominated by herbaceous species that can also be present under the bush canopies.

*R. sphaerocarpa* is a woody leguminous shrub with ephemeral leaves that grows up to 4 m tall and a diameter of 6 m, with cylindrical photosynthetic stems (cladodes). The shrub has an open canopy structure with an abundant grass substrate under the canopy, and a deep root system that can extract water from depths below 25 m (Domingo et al., 1999; Domingo et al., 2001; Haase et al., 1996). The period of growth starts in March, while flowering occurs in May, and fructification goes on from July to September. The germination of the new shoots takes place between January and February.

In the area selected, *R. sphaerocarpa* covered an average of 17% of the area ($f$), with an average leaf area index ($L_e$) of 0.81 m² m⁻².

Measurements and parameterisation of soil and plant resistances

To calculate the soil and plant resistances considered in the ML model (Fig. 1a), and used to calculate the effective resistances of the SL model, different parametric equations were used, relating these resistances with micrometeorological variables.

$r_s$ and $r_p$ were measured between DOY (day of year) 150 and 165 with microlysimeters, following the methodology proposed by Daamen et al. (1993). The measured values obtained were related with soil moisture ($\theta$), thus obtaining different parametric equations (Table 1).

For $r_s$ and $r_p$, we used the parametric equations obtained by Domingo et al. (1999), from measurements made with the method of the energy balance of heated sensors (McInnes et al., 1994; McInnes et al., 1996) in a near patch of *R. sphaerocarpa* at the bottom valley of the Rambla Honda field site. The measured values were related to wind speed at $z_c$ (u_c) as it is indicated in Table 1.

In the case of plant resistance $r_p$, most of the bibliography related to this resistance refers to its inverse, the plant conductance ($g_p$). The parametric equations used to calculate this conductance (Table 1) were the ones obtained by Brenner and Incoll (1997) in the same field site, relating $g_p^e$ to the flux of photosynthetically active radiation (Q), the water vapour pressure deficit at $z_c$ ($D_c$) and $\theta$. According to Baldocchi et al. (1991) the leaf conductance ($g_p^e$) can be calculated as:
Table 1 Parametric equations relating: (a) surface and aerodynamic resistances of soil ($r_s^g$ and $r_s^b$, respectively) and bare soil ($r_s^{g^b}$ and $r_s^{b^b}$, respectively) with soil moisture ($\theta$) and wind speed at reference height ($u_r$); (b) parameters $g_s^{max}$ and $b_s$ with $\theta$, taken from Brenner and Incoll (1997)

<table>
<thead>
<tr>
<th>Equations</th>
<th>$R^2$</th>
<th>$n$</th>
</tr>
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<tbody>
<tr>
<td>$r_s^g = 7.740^{0.195}$</td>
<td>0.90</td>
<td>23</td>
</tr>
<tr>
<td>$r_s^{g^b} = 0.450^{0.2}$</td>
<td>0.66</td>
<td>8</td>
</tr>
<tr>
<td>$r_s^b = 98.4u_t^{0.17}$</td>
<td>0.73</td>
<td>109</td>
</tr>
<tr>
<td>$r_s^{b^b} = 73.7u_t^{0.19}$</td>
<td>0.55</td>
<td>207</td>
</tr>
<tr>
<td>$b_s = -0.91\theta - 0.1$</td>
<td>0.98</td>
<td>4</td>
</tr>
<tr>
<td>$g_s^{max} = 2.10\theta + 0.33$</td>
<td>0.99</td>
<td>4</td>
</tr>
</tbody>
</table>

Brenner and Incoll (1997) related the daily average of the measured values of conductance with $D_t$ for different days, and the values of $g_s^{max}$ (maximum $g_s$ at light saturation, and water vapour saturation of air) and $b_s$ (that indicates how $g_s$ changes with $D_t$ obtained were related to $\theta$ (see equations in Table 1).

Once $g_s^e$ is known, and considering that $Q$ decreases through the canopy according to the coefficient of extinction of the canopy ($k$), $g_s^c$ is calculated as:

$$g_s^c = (g_s^e/k)\ln((b_q + \kappa Q)/(b_q + \kappa Q e^{k}))$$

following Shuttleworth and Gurney (1990), where $L_p$ is the leaf area index of the plant.

$r_s^g$ was calculated following the equations proposed by Shuttleworth and Wallace (1985) and Choudhury and Monteith (1988), where $r_s^g$ equals:

$$r_s^g = r_s^g/2L$$

being $r_s^g$ the average aerodynamic leaf resistance of the canopy leaves, calculated as:

$$r_s^g = (n/\alpha)(w/u_h)^{1.5} (1 - e^{-n/2})^{-1}$$

where $\alpha$ is a constant that relates $r_s^g$ with $u_h$ (Domingo et al., 1996), $w$ is the average width of the leaves and $u_h$ is the wind speed at canopy average height, calculated as:

$$u_h = (u_r/k)\ln((h - d)/z_0)$$

where $h$ is the height of vegetation, $d$ is the displacement height, $z_0$ is the roughness length and $k$ is the von Karman constant, and $u_r$ is the friction velocity calculated as:

$$u_r = ku_r/\ln((z_r - d)/z_0)$$

$r_s^g$ was also calculated with the theoretical equations developed by Shuttleworth and Gurney (1990) as:

$$r_s^g = (1/ku_r)\ln((z_r - d)/(h - d))(1 + \delta)$$

$$+ (h/nK_n)\left[e^{(n(1-h/d)/n)} - 1\right]$$

where $K_n$ is the turbulent diffusion coefficient for water vapour above the vegetation, $n$ is the coefficient indicating the decrease in the turbulent diffusion through the vegetation. $(1 + \delta)$ is an established stability correction factor taken from Shuttleworth and Shuttleworth and Gurney (1990) and analysed by Choudhury and Monteith (1988). $\delta$ is calculated as:

$$\delta = 5g(z_r - d)/(T_0 - T_r)$$

where $T_0$ is the temperature of air at $z_m$, calculated as:

$$T_0 = (A - \varepsilon E)/\rho c_p$$

Thus, an iteration of the ML model is needed to calculate $T_0$. $\varepsilon$ has a value of $-2$ for $\delta < 0$ and a value of $-0.75$ for $\delta > 0$ (Choudhury and Monteith, 1988).

The values of the vegetation and aerodynamic parameters needed to calculate these resistances are given in Table 2.

Micrometeorological measurements

The sensible and latent heat fluxes of the patch ($H$ and $L^*$, respectively) were measured with an Eddy covariance system located in a tower at $z_c$ (Table 2). The Eddy covariance system consisted of a three-dimensional sonic anemometer CSAT3 (Campbell Scientific Inc., Logan, USA) and a krypton hygrometer KH20 (Campbell Scientific Inc.), both connected to a datalogger (CR23X, Campbell Scientific Ltd, Logan, UT, USA). Measurements were made at a 10 Hz frequency, and the datalogger calculated and stored means, variances, and covariances every 30 min. $L^*$ measurements were corrected for air density fluctuations due to heat and water vapour flux as proposed by Webb et al. (1980). Hygrometer measurements were corrected for absorption of radiation by oxygen, according to Tanner et al. (1993). The rotation of the coordinate system (Kowalski et al., 1997) was unnecessary, because as the terrain is near a river bed, it is almost flat, and it was verified that the values barely changed with this correction.

The variables $u_r$ and $T_r$ were measured with the sonic anemometer. Although sonic anemometers measure sonic temperature, this temperature approximates very closely to virtual temperature (Kaimal and Gaynor, 1991), and virtual temperature is related to air temperature through the specific humidity. However, in the site of Rambla Honda

Table 2 Vegetation and aerodynamic parameters needed to calculate resistances: average vegetation height ($h$), roughness length ($z_0$), displacement height ($d$), leaf area index ($L$), fractional vegetation cover ($f$), and reference height ($z_r$), for the patch studied. All values in meters, except $L$ (in m$^2$ m$^{-2}$) and $f$. 

<table>
<thead>
<tr>
<th>$h$</th>
<th>$z_0$</th>
<th>$d$</th>
<th>$L$</th>
<th>$f$</th>
<th>$z_r$</th>
</tr>
</thead>
<tbody>
<tr>
<td>R. sphaerocarpa</td>
<td>2.26</td>
<td>0.23</td>
<td>1.76</td>
<td>0.81</td>
<td>0.17</td>
</tr>
</tbody>
</table>
the range of specific humidity is rather low and thus the difference between air temperature and virtual temperature is negligible.

The water vapour pressure at \( z_i \) (\( e_i \)), needed to calculate \( \Delta T_z \), was measured with a dew-point hygrometer (Dew-10, General Eastern Corp., USA). The \( R_h \), was measured with a NR Lite radiometer (Kipp and Zonen, Delft, The Netherlands) located at \( z_i \) (Table 2). Domingo et al. (2000) already indicated that, in a similar patch, this height enables measurements to be representative of the heterogeneity of the patch. \( G \), \( G_s \), and \( G_{bs} \) (soil heat flux of the patch, of soil under plant and of bare soil, respectively) were calculated, and related to \( R_h \), \( R_{n,s} \) and \( R_{n,bs} \), respectively, obtaining the parametric equations shown in Table 3. \( G \) and \( G_{bs} \) were calculated as the sum of the flux measured at a depth of 0.08 m (\( F \)) with soil heat flux plates (HFT-3, REBS, Seattle, WA, EEUU) and the heat stored in the layer of soil above the plates at \( z_s \) (Fuchs, 1986; Massman, 1992):

\[
S_t = \Delta T_t [B_o (C_t + C_w) Dp] / t
\]

where \( B_o \) is the apparent density of soil (1555 kg m\(^{-3}\)) according to Puigdefábregas et al. (1996), \( C_t \) is the specific heat of dry soil, \( C_w \) is the specific heat of water, \( Dp \) is the depth at which the soil heat flux plate is located, \( t \) is the time lapse between measurements, and \( \Delta T_t \) is the changing rate of soil temperature between two consecutive measurements. This last variable was measured with two thermo-couples (TCAV, Campbell Scientific Ltd.) located at two depths (0.02 and 0.06 m) above each soil heat flux plate. Two soil heat flux plates were located under a R. sphaerocarpa plant and other two on bare soil. The total soil heat flux of the patch (\( G \)) was calculated as the average of \( G \) and \( G_{bs} \), weighted by \( f \).

\( \theta \) was measured with 12 self-balanced impedance bridge (SBIB) probes at 0.04 m depth, displayed in a range of positions, from soil under plant to bare soil. This soil humidity sensor has been developed in the Estación Experimental de Zonas Áridas (C.S.I.C.) (Almería, Spain) (Vidal, 1994; Vidal et al., 1996) and used in previous works (see for instance Puigdefábregas and Sánchez, 1996; Domingo et al., 2000; Cantón et al., 2004).

All measurements of the micrometeorological variables (\( u_t \), \( T_r \), \( R_h \), \( F \), \( e \), \( \theta \), and \( T_t \)) were averaged every 30 min and recorded in data loggers (Campbell Scientific Ltd., Logan, UT, USA).

### Data set used

Both the SL model and the ML model were run for a set of 30 min data of 11 days, corresponding to DOY 53–55 and 64–71 (comprised between the 21st of February and the 12th of March). To be able to compare the estimated data with the measured data, the data set used was filtered following different criteria. In the first place, the days that lacked data for any of the energy fluxes necessary to analyse the energy balance (i.e., \( R_h \), \( G \), \( \dot{E}^t \) and \( H \)) were eliminated. Data where \( R_h \) was negative were also eliminated, leaving only the daytime data (from 8:00 to 16:00 h), because the behaviour of the heat fluxes at night-time under stable conditions is erratic and difficult to predict. Data from rainy days were also eliminated because there is condensation on the krypton hygrometer, which generates poor \( \dot{E} \) data. Also, some days after a rainfall event generated inconsistent relations between micrometeorological variables and evapotranspiration fluxes, the analysis of which is beyond the scope of this work. Therefore, these days were also eliminated. Finally, we selected a set of data with values of diurnal \( \dot{E} \) high enough to be reliable, eliminating negative \( \dot{E}^t \) values, or \( \dot{E}^t \) values near to 0 W m\(^{-2}\), which are typical of cloudy days, or days from the dry season.

To assess the accuracy of the measured \( \dot{E}^t \) values, the energy balance of the fluxes was analysed with a regression between the measured available energy (\( R_h - G \)) and the sum of the turbulent fluxes (\( \dot{E}^t + H \)) for the study period (Fig. 2). The data showed an acceptable energy balance closure, practically 90% (\( b = 0.88 \), \( R^2 = 0.87 \)).

To check whether the turbulent fluxes measured by the Eddy covariance system were representative of the two patches under study, a footprint analysis was done with the Flux Source Area Model (FSAM) of Schmid (1994, 1997). An analysis of the 50% source areas for a range of atmospheric stabilities indicated that the source area of the turbulent fluxes measured was widely within the patch-area (see Were et al., 2007 for more details on the footprint analysis). However, as the Eddy covariance tower was located at the North of the patch (as indicated in the Micrometeorological measurements section), there might be some source areas not representative for wind directions coming from the North. However, an analysis of the wind

---

**Table 3** Parametric equations obtained by relating the total soil heat flux (\( G \)), soil under plant heat flux (\( G_s \)) and bare soil heat flux (\( G_{bs} \)) of the patch, with their respective net radiations (\( R_{n,s} \) and \( R_{n,bs} \)), with their respective net radiations (\( R_{n,s} \) and \( R_{n,bs} \))

<table>
<thead>
<tr>
<th>Equations</th>
<th>( R^2 )</th>
<th>( n )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( G )</td>
<td>0.29( R_{n,s} ) – 8.29</td>
<td>0.72</td>
</tr>
<tr>
<td>( G_s )</td>
<td>0.34( R_{n,s} ) – 12.04</td>
<td>0.72</td>
</tr>
<tr>
<td>( G_{bs} )</td>
<td>0.24( R_{n,bs} ) – 12.04</td>
<td>0.72</td>
</tr>
</tbody>
</table>

**Figure 2** Comparison of the turbulent fluxes (\( \dot{E}^t + H \)) with the available energy (\( R_h - G \)) measured in the studied patch \( n = 177 \). The regression line forced by the origin is indicated (straight line), as well as the 1:1 line (dashed line).
directions of the 30 min data indicated that only 5% of the wind directions were within the NW—NE directions, while 80% of the wind directions were within the SW—SE directions. Therefore, it was considered that the measured turbulent fluxes were highly representative of the patch studied.

Results

Soil surface or aerodynamic resistances were higher than the respective plant resistances, as can be seen from a comparison between the average of the soil and plant resistances for the study period (Table 4). When comparing surface and aerodynamic resistances, we found that the aerodynamic resistances were lower than the surface ones, both for soil and plant resistances and for the effective resistances (Table 4). In the case of the different effective aggregated resistances \( \left( r^e_i \right) \), those aggregated in parallel were lower than those aggregated in series (60% and 40% lower for the aerodynamic and surface resistances, respectively).

The regression between \( \mathcal{E} \) estimated with the ML model and measured (Fig. 3) was highly significant both for the 30 min and the daily values (Table 5).

Comparing the daily values of the partial \( \mathcal{E} \) for the different sources (Fig. 4), it is clear that the source that contributes most to the total \( \mathcal{E}^E_{SL} \) is bare soil, since \( \mathcal{E}^E_{SL} \) can represent from 69% to 81% of \( \mathcal{E}^E_{SL} \).

The estimated \( \mathcal{E}^i_{SL} \) values obtained with the SL model using different combinations of \( \left( r^a_i \right) \) and \( \left( r^s_i \right) \) were plotted against the \( \mathcal{E}^i \) measured values (Fig. 5), and the values of regression parameters were compared (Table 5). The values of slope \( b \) varied from 0.40 (30 min values) and 0.46 (daily values) for \( \mathcal{E}^i_{SL} \) calculated with \( \left( r^s_i \right) \) and \( \left( r^s_i \right) \) to 0.80 (30 min values) and 0.73 (daily values) for \( \mathcal{E}^i_{SL} \) calculated with \( \left( r^a_i \right) \) and \( \left( r^a_i \right) \). The highest \( R^2 \) was obtained also for \( \mathcal{E}^i_{SL} \) calculated with \( \left( r^s_i \right) \) and \( \left( r^s_i \right) \) \((R^2 = 0.77 \text{ for 30-min values, and } 0.76 \text{ for daily values})\).

To determine the magnitude of the differences between the estimated and measured values of \( \mathcal{E} \) we calculated the root mean square error (RMSE):

\[
\text{RMSE} = \sqrt{(\mathcal{E}^i_{\text{measured}} - \mathcal{E}^i_{\text{estimated}})^2}
\]

Results are shown in Table 6.

For estimates obtained with the ML model the RMSE for the 30 min values was 0.012, and 0.134 for the daily values. In the case of estimated \( \mathcal{E}^i_{SL} \), the lowest RMSE was obtained for \( \mathcal{E}^i_{SL} \) calculated with \( \left( r^s_i \right) \) and \( \left( r^s_i \right) \) (0.011 for 30-min values and 0.08 for daily values), while the highest RMSE was obtained for \( \mathcal{E}^i_{SL} \) calculated with \( \left( r^a_i \right) \) and \( \left( r^a_i \right) \) (0.027 for 30 min values and 0.378 for daily values).

In general, the lower values of RMSE were obtained when using the effective surface resistances aggregated in parallel \( \left( r^a_i \right) \). Regarding only the effective aerodynamic aggregated resistances, the lower RMSE were obtained when using the effective aerodynamic resistance aggregated in series \( \left( r^s_i \right) \).

Comparing \( \mathcal{E}^i_{ML} \) and \( \mathcal{E}^i_{SL} \) using \( \left( r^s_i \right) \) and \( \left( r^s_i \right) \), the averaged differences obtained were 8.7% (SD = 6.4%) for the 30 min values, and 10.8% (SD = 7.1%) for the daily values. The highest difference between \( \mathcal{E}^i_{ML} \) and \( \mathcal{E}^i_{SL} \) was obtained

### Table 4

Average and standard deviation (SD) of the 30 min data \( (n = 177) \) for: (a) aerodynamic and surface resistances of plant \( \left( r^a_i \right) \) and \( \left( r^s_i \right) \), soil under plant \( \left( r^a_i \right) \) and \( \left( r^s_i \right) \); \( \left( r^a_i \right) \) and \( \left( r^s_i \right) \), as well as the aerodynamic resistance between the soil and \( \left( r^a_i \right) \); (b) effective aerodynamic and surface resistances of the patch, aggregated in parallel \( \left( \left( r^a_i \right) \right) \), series \( \left( \left( r^s_i \right) \right) \), and an average of both \( \left( \left( r^a_i \right) \right) \), \( \left( \left( r^s_i \right) \right) \).

<table>
<thead>
<tr>
<th>Aerodynamic resistances</th>
<th>( r^a_i )</th>
<th>( r^s_i )</th>
<th>( r^a_i )</th>
<th>( r^s_i )</th>
<th>( r^a_i )</th>
<th>( r^s_i )</th>
<th>( r^a_i )</th>
<th>( r^s_i )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average</td>
<td>5.7</td>
<td>88.2</td>
<td>65.3</td>
<td>10.3</td>
<td>28.19</td>
<td>80.4</td>
<td>54.30</td>
<td></td>
</tr>
<tr>
<td>SD</td>
<td>2.3</td>
<td>9.7</td>
<td>8.1</td>
<td>8.5</td>
<td>7.5</td>
<td>16.6</td>
<td>12.3</td>
<td></td>
</tr>
<tr>
<td>Surface resistances</td>
<td>( r^a_i )</td>
<td>( r^s_i )</td>
<td>( r^a_i )</td>
<td>( r^s_i )</td>
<td>( r^a_i )</td>
<td>( r^s_i )</td>
<td>( r^a_i )</td>
<td>( r^s_i )</td>
</tr>
<tr>
<td>Average</td>
<td>307.3</td>
<td>1022.2</td>
<td>553.5</td>
<td>424.6</td>
<td>685.4</td>
<td>555</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SD</td>
<td>196.6</td>
<td>333.4</td>
<td>290.7</td>
<td>187.6</td>
<td>306.9</td>
<td>246.2</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

All resistances are in \( \text{m s}^{-1} \).

![Figure 3](image.png)

**Figure 3** Regression between measured \( \mathcal{E} \) and the values estimated with the ML model \( \left( \mathcal{E}^i_{ML} \right) \) for: (a) 30-min values and (b) total daily values. The solid line indicates the regression line and the dashed line represents the 1:1 line.
Regressions between Figure 5

Daily values of measured \( E \) and estimated \( \hat{E}_{\text{ML}} \) and \( \hat{E}_{\text{SL}} \) calculated using different aggregated effective resistances, for the 30-min data (\( n = 177 \)) and the daily totals (\( n = 11 \)).

<table>
<thead>
<tr>
<th></th>
<th>30 min</th>
<th>Daily totals</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>( b )</td>
<td>( a )</td>
</tr>
<tr>
<td>( \hat{E}_{\text{ML}} )</td>
<td>0.71</td>
<td>0.01</td>
</tr>
<tr>
<td>( \hat{E}<em>{\text{SL}} (r^e</em>{\text{p}}) )</td>
<td>0.51</td>
<td>0.01</td>
</tr>
<tr>
<td>( \hat{E}<em>{\text{SL}} (r^e</em>{\text{s}}) )</td>
<td>0.67</td>
<td>0.01</td>
</tr>
<tr>
<td>( \hat{E}<em>{\text{SL}} (r^e</em>{\text{p}} + r^e_{\text{s}}) )</td>
<td>0.80</td>
<td>0.01</td>
</tr>
<tr>
<td>( \hat{E}<em>{\text{SL}} (r^e</em>{\text{p}} + r^e_{\text{s}}) )</td>
<td>0.40</td>
<td>0.01</td>
</tr>
<tr>
<td>( \hat{E}<em>{\text{SL}} (r^e</em>{\text{p}} + r^e_{\text{s}}) )</td>
<td>0.54</td>
<td>0.01</td>
</tr>
<tr>
<td>( \hat{E}<em>{\text{SL}} (r^e</em>{\text{p}} + r^e_{\text{s}}) )</td>
<td>0.65</td>
<td>0.01</td>
</tr>
</tbody>
</table>

The level of significance \( p \) of \( R^2 \) is indicated: ** \( p < 0.01 \), * \( p < 0.05 \).

Table 5

RMSE obtained comparing measured \( E \) and \( \hat{E}_{\text{ML}} \) or \( \hat{E}_{\text{SL}} \) obtained using different combinations of the aggregated effective resistances.

<table>
<thead>
<tr>
<th>RMSE</th>
<th>30 min</th>
<th>Daily totals</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \hat{E}_{\text{ML}} )</td>
<td>0.012</td>
<td>0.134</td>
</tr>
<tr>
<td>( \hat{E}<em>{\text{SL}} (r^e</em>{\text{p}}) )</td>
<td>0.020</td>
<td>0.264</td>
</tr>
<tr>
<td>( \hat{E}<em>{\text{SL}} (r^e</em>{\text{s}}) )</td>
<td>0.014</td>
<td>0.153</td>
</tr>
<tr>
<td>( \hat{E}<em>{\text{SL}} (r^e</em>{\text{p}} + r^e_{\text{s}}) )</td>
<td>0.011</td>
<td>0.080</td>
</tr>
<tr>
<td>( \hat{E}<em>{\text{SL}} (r^e</em>{\text{p}} + r^e_{\text{s}}) )</td>
<td>0.027</td>
<td>0.378</td>
</tr>
<tr>
<td>( \hat{E}<em>{\text{SL}} (r^e</em>{\text{p}} + r^e_{\text{s}}) )</td>
<td>0.020</td>
<td>0.276</td>
</tr>
<tr>
<td>( \hat{E}<em>{\text{SL}} (r^e</em>{\text{p}} + r^e_{\text{s}}) )</td>
<td>0.015</td>
<td>0.193</td>
</tr>
</tbody>
</table>

RMSE was calculated for the 30-min data (\( n = 177 \)) and for the daily totals (\( n = 11 \)).

Figure 4 Daily values of measured \( \dot{E} \) (columns), estimated \( \hat{E}_{\text{ML}} \) (\( \Delta \)), and the partial \( \dot{E} \) of each source \( \dot{E}^{\text{p}} \) (\( \Theta \)), \( \dot{E}^{\text{s}} \) (\( \bigcirc \)) and \( \dot{E}^{\text{a}} \) (\( \bullet \)).

Figure 5 Regressions between \( \dot{E} \) estimated with the SL model (\( \hat{E}_{\text{SL}} \)) and the measured \( \dot{E} \) for: 30-min values, \( n = 177 \) (graphs on the left) and total daily values, \( n = 11 \) (graphs on the right). \( \hat{E}_{\text{SL}} \) was estimated using different combinations of surface and aerodynamic effective resistances: \( r^e_{\text{p}} \) and \( r^e_{\text{s}} \) (\( \Theta \)); \( r^e_{\text{p}} + r^e_{\text{s}} \) (\( \bigcirc \)); \( r^e_{\text{p}} + r^e_{\text{s}} \) (\( \bigotimes \)); \( r^e_{\text{p}} + r^e_{\text{s}} + r^e_{\text{a}} \) (\( \blacksquare \)); \( r^e_{\text{p}} + r^e_{\text{s}} + r^e_{\text{a}} + r^e_{\text{a}} \) (\( \square \)). The regression lines are indicated (thick lines for \( \hat{E}_{\text{SL}} \) calculated with \( r^e_{\text{p}} \), thin lines for \( \hat{E}_{\text{SL}} \) calculated with \( r^e_{\text{s}} \), and thin dashed lines for \( \hat{E}_{\text{SL}} \) calculated with \( r^e_{\text{a}} \)), as well as the 1:1 lines (thick dashed lines).
using \((\bar{r}_s^e)\) and \((\bar{r}_a^e)\), with averaged differences of 40.9% (SD = 9.4%) for the 30-min values, and 38.5% (SD = 2.3%) for the daily values.

**Discussion**

The two models used in this work to estimate \(\lambda E\) at patch-scale are based on the Penman–Monteith approach (Monteith, 1965), which considers that \(\lambda E\) depends on the energy balance of the patch and on a gradient of vapour concentrations controlled by a series of surface and aerodynamic resistances.

However, in the multi-layer approach (ML), the heterogeneity of the patch due to the sparseness of the vegetation is solved by partitioning the energy balance and the resistances into different sources of \(\lambda E\) (plant, soil under plant and bare soil). This approach gives way to a fairly complex model, needing iterations, although it takes into account the different effects of vegetation and soil on \(\lambda E\), as well as the effect of advection by considering that plant and soil interact at a height \(z_m\).

In the case of the single-layer approach (SL), the effect of the heterogeneity of the patch in the estimation of \(\lambda E\) is simplified by considering this heterogeneity only at the level of the resistances. In this model, the resistances used are effective resistances calculated by aggregating the resistances of soil and plant. The rest of the variables are considered fixed at the \(z_e\) level, which reduces considerably the complexity of the model. However, this simplification does not take into account explicitly the effect of advection between plant and soil.

Analysing the different resistances we noticed that the surface resistances, either from soil and plant or effective, were higher than the aerodynamic resistances. Therefore they have a remarkable effect on the modelling of \(\lambda E\), as indicated by other authors (Verhoef and Allen, 1998).

In the case of the resistances of soil and plant, bare soil is the main source of evapotranspiration due to the low \(f\) of the patch, and the parameterisation of its resistances, especially of the bare soil surface resistance \((\bar{r}_s^m)\), is very important.

If we compare the effective resistances obtained with the different types of aggregation, as expected, the resistances aggregated in parallel are lower than the ones aggregated in series (or the average of aggregating in series and in parallel). However, in the case of the effective surface resistances, those aggregated in series are not used in the SL model because this type of aggregation has no physical explanation, according to the network resistances. Were et al. (2007) already have indicated that this type of aggregation produces severe underestimation of \(\lambda E\).

A comparison of the different estimates of \(\lambda E_{SL}^a\) with the measured values showed clearly that the estimates that are most similar to the observed are obtained with the effective resistances \((\bar{r}_s^e)\) and \((\bar{r}_a^e)\). \(\lambda E_{SL}^a\) calculated with \((\bar{r}_s^e)\) was clearly more similar to the measured values than \(\lambda E_{SL}^a\) calculated with \((\bar{r}_a^e)\). First, these results show that the adequate type of aggregation is not the same for surface and aerodynamic resistances. As Blyth et al. (1993) already indicated, the type of aggregation of the resistances depends on the type of resistance and the flux. Also, these results do not support the idea (proposed by Blyth et al. (1993) and used by other authors (Dolman and Blyth, 1997)) that, in the case of the effective surface resistances, the average of effective resistances aggregated in series and in parallel \((\bar{r}_a^e)\) would generate better estimates of \(\lambda E\). Using both \((\bar{r}_s^e)\) and \((\bar{r}_a^e)\), the RMSE obtained was higher than the RMSE obtained for most of the other resistance combinations.

The use of \((\bar{r}_s^e)\) and \((\bar{r}_a^e)\) clearly underestimated the measured \(\lambda E\) of the patch. It should be noticed that for estimating \(\lambda E\), Blyth et al. (1993) studied the aggregation of resistances of two patches with theoretical values of their resistances, while in our work we have analysed the aggregation of soil and plant resistances, and always using measured, realistic values. These differences may explain the different results obtained in the aggregation of resistances.

Comparing the estimates obtained with the ML model, and the SL model using the effective surface resistance aggregated in parallel \((\bar{r}_s^e)\) and the effective aerodynamic resistance aggregated in series \((\bar{r}_a^e)\), it can be observed that both estimates are quite similar to the measured \(\lambda E\), being SL estimates even more similar to the measured values than ML estimates. This is an interesting result, since the SL model does not consider the effect of the advection in the patch. Moreover, the difference between both estimates was only of around 10%.

These results indicate that, for our study area, with sparse-vegetation and under semi-arid climate, when modelling \(\lambda E\) at patch-scale the parameterisation done to calculate the resistances of soil and plant is more important than the use of a multi-layer or a single-layer model. The main advantage of using a single-layer model is the absence of iterations, and a simpler mathematical framework.

The main difference between these two types of models is that the multi-layer model considers a within canopy height \((z_m)\) at which all sources interact, calculating temperature and water vapour pressure deficit at this height, while the single-layer model only considers these variables at the reference height \((z_e)\). Therefore, it is logical to think that with high differences between these variables at \(z_m\) and \(z_e\), the differences between using a multi-layer or a single-layer model would be higher too. It would be expected that, in certain climatic conditions, as the fraction of vegetation of a patch decreases, the interaction between the sources also decreases, and therefore the coupling with the surface atmospheric layer increases. Moreover, the lack of vegetation results in a decrease in the roughness of the surface and therefore in the proximity of \(z_m\) and \(z_e\). According to this, for certain climatic conditions, a decrease in the fractional vegetation cover results in a decrease of the differences between variables at \(z_m\) and \(z_e\), and therefore in low differences between using a multi-layer or a single-layer model.

The results from this paper are important because they show that, for a range of areas with low fractional vegetation cover, aggregating the heterogeneity of an area by using effective aggregated resistances produces estimates of \(\lambda E\) even more accurate than the ones obtained using a sparse-vegetation model that considers the different sources of \(\lambda E\) interacting at a within canopy height. This is promising because it shows that the use of aggregated effective resistances does not introduce an important error in the estimation of \(\lambda E\), representing patch-scale heteroge-
neity with acceptable accuracy when used in higher scale models.

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