



Sensitivity of biogenic carbon and heat fluxes to urban vegetation parametrisations in the urban land surface model SUEWS

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Abstract. As cities are taking actions to reduce their carbon dioxide (CO₂) emissions, the potential of urban vegetation to act as a carbon sink has received increasing attention. Carbon sequestration, however, has large uncertainties due to the highly variable and mosaic nature of urban vegetation. For land surface models to realistically estimate carbon sinks in urban areas, they need to be able to describe various urban vegetation types and their responses to environmental controls. One such model is the Surface Urban Energy and Water balance Scheme (SUEWS), which is an urban land surface model that can simulate energy, water and CO₂ exchanges in cities. For SUEWS to accurately simulate the biogenic CO₂ fluxes, it requires information on surface conductance controlling stomatal opening, maximum photosynthesis values, and parameters for soil and vegetation respiration. The main aims of this study are to provide a more comprehensive set of vegetation parameters derived from eddy covariance and chamber observations to extend the usability of SUEWS in different cities, and to evaluate the selection of the specific vegetation parameters on SUEWS model performance in two mid-latitude cities: Swindon (UK) and Minneapolis (US).

The results highlight the importance of appropriate selection of surface conductance, maximum photosynthesis, and soil and vegetation parameters for different types of vegetation to be able to accurately simulate the biogenic and net carbon fluxes at monthly and annual level. Surface conductance parameters are most affected by soil moisture and specific humidity, rather than radiation and air temperature. The model performs better with tree surface conductance parameters ($R = 0.62\text{--}0.70$ in Swindon, $R = 0.61\text{--}0.74$ in Minneapolis) than lawn or low vegetation parameters ($R \leq 0.48$ in Swindon, $R \leq 0.72$ in Minneapolis), even in areas with smaller tree cover, highlighting the significance of urban trees in controlling overall stomatal conductance. The sensitivity of CO₂ fluxes to parameter selection is greater than that of latent heat fluxes with R ranging between $-0.26\text{--}0.74$ when compared to $0.60\text{--}0.90$. Carbon balances are influenced by traffic levels, air temperatures, and rates of photosynthesis and soil respiration. Overall, the findings emphasize the necessity for accurate observations of urban vegetation to effectively parameterise urban vegetation and soil, as using inappropriate reference vegetation can lead to substantial errors in estimating biogenic carbon exchanges.



1 Introduction

Urbanization is a multifaceted transformation that significantly alters natural landscapes, impacting surface properties and driving changes in land-atmosphere interactions. The rapid expansion of urban areas implies profound effects on surface processes, including energy, water, and carbon cycles (Nordbo et al., 2013; Ward et al., 2013; Ward and Grimmond, 2017). The associated changes extend beyond the local scale, contributing to broader phenomena such as the urban heat island, flooding and cloud formation (Oke, 1982; Rodriguez et al., 2003; Theeuwes et al., 2022). In other words, understanding the modified land surface processes and the corresponding land-atmosphere interactions is crucial for accurately assessing the environmental impacts of urban landscape, which in turn provides essential information for developing effective strategies to mitigate the adverse climate effects of urbanization and to enhance the sustainability of cities.

In recent years, the interest in urban land-surface interactions has particularly been in the carbon cycle as increasing number of cities are interested in monitoring and reducing their carbon dioxide (CO₂) emissions (Lian et al., 2023; Aigner et al., 2026). Here, biogenic CO₂ components, including photosynthesis and soil and vegetation respiration, also play an important role. Accounting for these processes is essential to reduce uncertainties in anthropogenic CO₂ emission estimates, as atmospheric observations capture both anthropogenic and biogenic signals simultaneously. This distinction is particularly important in cities, where carbon sinks can contribute significantly to climate mitigation efforts (Lauvaux et al., 2020; Hautamäki et al., 2025). There are multiple modelling approaches allowing researchers to better understand the role of urban vegetation in sequestering CO₂ and contributing to the carbon balance of cities (Stagakis et al., 2025; Thölix et al., 2025). VPRM (The Vegetation Photosynthesis and Respiration Model, Mahadevan et al., 2008), urban-VPRM (Hardiman et al., 2017), diFUME (Stagakis et al., 2022) and SMUrF (Wu et al., 2021) are examples of empirical and light use efficiency models that capture the dynamics of vegetation based on satellite observations, whereas SUEWS (Järvi et al., 2019), SURFEX (Goret et al., 2019) and JSBACH (Reick et al., 2013) are examples of process or semi-process based land surface models. While the satellite-based approaches (Miller et al., 2018) have been found advantageous for example as part of model inversion systems, they are tied to present conditions. Land surface models on the other hand can be used to estimate future or scenario-based carbon exchange in cities (Havu et al., 2024). They have also become important tools for understanding urban surface-atmosphere interactions more widely as they offer a mean to simulate the exchanges of energy, water, and CO₂ integratively.

The Surface Urban Energy and Water Balance Scheme (SUEWS, Järvi et al., 2011) has been extensively applied and evaluated in multiple cities around the world in simulating energy, water and carbon cycles (e.g., Demuzere et al., 2017; Zheng et al., 2023; Obe et al., 2024). SUEWS was originally developed for water and energy balances but has since been extended to CO₂ exchange including both anthropogenic and biogenic components (Järvi et al., 2019). The capability of SUEWS in simulating urban land surface-atmosphere interactions relies on commonly measured meteorological observations and on parameterisation of the surface and its processes. In particular, accurate representation of surface conductance describing stomatal control (Jarvis, 1976) and leaf area index (LAI) development are essential to capture the behaviour of different types of urban vegetation (Garuma, 2018; Havu et al., 2022; Omidvar et al., 2022; Zheng et al., 2023) and thus in simulating photosynthesis, evapotranspiration and latent heat fluxes (LE). However, obtaining appropriate conductance and LAI parameters for urban veg-



etation can be challenging due to lack of observations from urban vegetation. Most of the parameters used in SUEWS are those from natural vegetation in temperate climates (Breuer et al., 2003) which are not always suitable to describe highly variable urban vegetation (Havu et al., 2022, 2024).

60 To enhance the applicability of SUEWS for simulating urban vegetation in different cities, this study aims to examine the impact of surface conductance, photosynthesis and soil and vegetation respiration parameters on modelled CO₂ and latent heat fluxes and to evaluate the model performance against urban eddy covariance (EC) measurements in mid-latitude suburban neighbourhoods in Swindon (UK) and Minneapolis (USA). For this, the study combines a comprehensive set of surface conductance and photosynthesis parameters derived from eddy covariance (EC) and chamber measurements made in different
65 urban and natural vegetation types.

2 Methods and material

2.1 Site description

2.1.1 Swindon, UK

The first evaluation neighbourhood is a residential area (Fig. 1a) in the town of Swindon, located 120 km west of London.
70 EC measurements of energy fluxes and CO₂ were conducted at the site in 2011–2013 (51°35' N, 1°48' W) approximately 3 km north of Swindon town centre (Ward et al., 2013). The area has high vegetation cover of 44% within a 500 m radius of the EC tower (Table 1). Grass is the most dominant vegetation type with 36% areal contribution while deciduous trees cover 8% and evergreen trees only 1%. Most of the vegetation is within gardens, parks, green corridors and alongside roads. The typical height of trees in the area is 6.2 meters. Most buildings within the 500 m radius circle consist of one to two stories, with
75 the mean building height of 4.2 m. Housing arrangements are typical of suburban areas in the UK. Paved surfaces cover 33% and buildings 16% of the total surface. The population density is approximately 4700 inhabitants per square kilometer (ONS, 2011).

The EC setup consisted of a 3D sonic anemometer (R3, Gill Instruments, Lymington, UK) for sonic temperature and wind measurements, and an open-path infrared gas analyser (LI-7500, LI-COR Biosciences, Lincoln, USA) for water vapour and
80 CO₂ mixing ratios at a height of 12.5 m. A four-component radiometer (NR01, Hukseflux Thermal Sensors, Delft, the Netherlands) measured incoming and outgoing longwave ($L_{\downarrow}$ and $L_{\uparrow}$) and shortwave ($K_{\downarrow}$ and $K_{\uparrow}$) radiation at a height of 10.1 m. Additional meteorological variables were measured by an automatic weather station (WXT510, Vaisala, Finland) at a height of 10.6 m. More information of the site and the measurements can be found in Ward et al. (2013).



Figure 1. Aerial images (Google Earth, 2026) showing the model evaluation sites in (a) Swindon, UK ($51^{\circ}35' \text{ N}$, $1^{\circ}48' \text{ W}$) and (b) Minneapolis, US ($44^{\circ}59' \text{ N}$, $93^{\circ}11' \text{ W}$). The red circles indicate the modelled area which is approximate source area of the measurements within 500 m radius around the EC towers marked by yellow stars. Note that in Minneapolis only the residential area was considered in this study.

Table 1. Characteristics of the Swindon and Minneapolis study areas used in the SUEWS model simulations. For Minneapolis, only the simulated residential area parameters are given.

Variable	Swindon	Minneapolis
Location	$51^{\circ}35' \text{ N}$, $1^{\circ}48' \text{ W}$	$44^{\circ}59' \text{ N}$, $93^{\circ}11' \text{ W}$
Surface fraction of paved surfaces (fr_{paved})	0.33	0.08
Surface fraction of buildings (fr_{bldg})	0.16	0.12
Surface fraction of grass (fr_{grass})	0.36	0.39
Surface fraction of deciduous trees (fr_{decTr})	0.08	0.30
Surface fraction of evergreen trees (fr_{everTr})	0.01	0.06
Surface fraction of bare soil (fr_{bareS})	0.06	0.00
Surface fraction of water areas (fr_{water})	0.00	0.04
Population density on weekday ($p_{h,wd}$, ha^{-1})	47.63	10
Population density on weekend ($p_{h,we}$, ha^{-1})	47.63	10
Traffic rate weekday (Tr_{we} , $\text{veh km m}^{-2} \text{ day}^{-1}$)	0.08578	0.007130
Traffic rate weekend (Tr_{wd} , $\text{veh km m}^{-2} \text{ day}^{-1}$)	0.066577	0.004870
Mean building height (m)	4.2	6
Mean tree height (m)	6.2	12
Roughness length (m)	0.5	0.76 ^a
Displacement height (m)	3.5	5.36 ^a

^a Values calculated in SUEWS.



2.1.2 Minneapolis–Saint Paul, US

85 The second evaluation site is a suburban neighbourhood (Fig. 1b) in Minneapolis, where an EC tower (44°59' N, 93°11' W) measuring energy and CO₂ fluxes was operational between 2006–2009 (Peters et al., 2011; Menzer and McFadden, 2017). The surroundings include a residential neighbourhood north of the EC tower and a recreational area in the south, but in this study data only from the residential area are used. The area mostly consists of detached single-family houses with a mean height of 6 m. A large fraction (75%) of the surface is vegetated, with grass surfaces covering 39%, deciduous trees 30% and evergreen
90 trees 6% (Table 1). The mean tree height is 12 m. Buildings represent 12% and paved surfaces 8% of the surface. Water bodies make up the remaining 4%. The population density is low, with 1000 inhabitants per km². Weekday traffic rate in the area is 0.00713 veh km m⁻² day⁻¹ and the weekend traffic rate 0.00487 veh km m⁻² day⁻¹.

The EC measurements were conducted with a 3D sonic anemometer (CSAT3, Campbell Scientific, Inc., Logan, Utah, USA) for sonic temperature and wind, and a closed-path infrared gas analyzer (LI-7000, LI-Cor, Lincoln, Nebraska, USA) for water
95 vapour and CO₂ mixing ratios at 40 m above ground level. Although the measurement height is greater in Minneapolis than in Swindon, the higher surface roughness and slight differences in the definition of the average source area result in smaller effective source area of approximately 500 m. Several meteorological variables including wind speed and direction, air temperature and relative humidity (derived from air temperature) were measured in the tower at 40 m height (Peters et al., 2011). Net all-wave radiation was measured at 150 meters above ground (CNR1, Kipp and Zonen, Delft, Netherlands). Atmospheric
100 pressure and precipitation were measured at Minneapolis-Saint Paul International Airport and University of Minnesota climate station (Peters et al., 2011). More information about the measurements and site can be found from Menzer and McFadden (2017).

2.2 Model physics and parameterisation

2.2.1 Surface Urban Energy and Water Balance Scheme (SUEWS)

105 SUEWS is an urban land surface model used to simulate surface energy, water balances, and CO₂ fluxes at a local scale (Järvi et al., 2011, 2019). This model characterizes the heterogeneous urban surface into pervious (evergreen trees/shrubs, deciduous trees/shrubs, grass, bare soil), impervious (buildings, paved) and water, allowing a mix of these seven land covers within a grid cell. SUEWS requires input on surface information such as surface cover fractions and building and tree heights, and common meteorological forcing variables including air temperature (T_{air}), air pressure (p), wind speed (U), relative humidity (RH),
110 incoming solar radiation ($K_{\downarrow}$) and precipitation. SUEWS has sub-models for net all-wave radiation, storage and heat fluxes, snow, and irrigation. Among them the CO₂ module (Järvi et al., 2019) is designed for simulating the local-scale CO₂ surface fluxes (F_C). F_C is determined with a bottom-up approach, taking into account both anthropogenic (F_{ant}) and biogenic (F_{bio}) components following

$$F_C = F_{ant} + F_{bio} = (F_M + F_V + F_B + F_P) + (F_{pho} + F_{res}), \quad (1)$$



115 where F_M are CO₂ emissions from human metabolism, F_V emissions from traffic, F_B emissions from buildings (e.g., combustion of natural gas, coal, wood), F_P emissions from local-scale point sources, F_{pho} is CO₂ uptake by photosynthesis and F_{res} is CO₂ release by vegetation and soil respiration. Positive values indicate sources of CO₂ while negative values indicate sinks of CO₂ with respect to the atmosphere. The CO₂ absorption and release over water surfaces are not currently accounted for. For the anthropogenic CO₂ components, refer to Appendix A for details.

120 2.2.2 Parameterisation of biogenic CO₂ components

In SUEWS, stomatal control is described using an empirical surface conductance model (Järvi et al., 2011) controlling both the canopy-level photosynthesis and evapotranspiration. For photosynthesis, the model has a form:

$$F_{pho} = \sum_i (f r_i F_{pho,max,i} LAI_i) g(K_{\downarrow}) g(T_{air}) g(\Delta q) g(\Delta \theta), \quad (2)$$

where the maximum potential photosynthesis ($F_{pho,max,i}$) for different vegetation type i is scaled with leaf area index (LAI_i , 125 m² m⁻²), and multiplied by environmental response functions $g(K_{\downarrow})$, $g(T_{air})$, $g(\Delta q)$, and $g(\Delta \theta)$ for incoming shortwave radiation, air temperature, specific humidity deficit, and soil moisture deficit, respectively (Järvi et al., 2019, Appendix B). Evapotranspiration is calculated from the modified Penman-Monteith equation where the surface resistance is described using similar form to Eq. 2, but with $F_{pho,max,i}$ replaced with maximum conductance for each vegetation type (Järvi et al., 2011; Ward et al., 2016).

130 The soil and vegetation respiration F_{res} (μmol m⁻² s⁻¹) is modelled based on an exponential increase with air temperature and empirical values a and b in the form of

$$F_{res} = \sum_i f r_i \max(a_i \cdot \exp(T_{air} b_i), 0.6) \quad (3)$$

with 0.6 as the lower limit F_{res} in winter periods (Järvi et al., 2019).

2.3 Parameters for surface conductance, maximum photosynthesis and respiration

135 Selecting appropriate parameters for the different vegetation types (deciduous trees/shrubs, evergreen trees/shrubs, and grass) is important in order to reduce vegetation related modelling uncertainties. The vegetation type specific parameters $F_{pho,max,i}$ and G_2 - G_6 in Eq. 2 and a_i and b_i in Eq. 3 vary in different environments such as forests, street-side, parks, lawns and meadows. Here we examine parameter values obtained from previous studies as well as derive new ones (Table 2) using the same approaches as in earlier studies (Järvi et al., 2019; Havu et al., 2024; Stagakis et al., 2025).

140 2.3.1 Parameters for trees

The deciduous forest (DF) and evergreen forest (EF) parameters for photosynthesis and soil and vegetation respiration were derived in Havu et al. (2024) using EC data from the Harvard Forest, US (42°54'N, 72°17'W) representative of deciduous broadleaved forest dominated by red maple and red oak (Goulden et al., 1996), and from a Scots pine dominated coniferous



145 forest in Hyytiälä, southern Finland (61°51'N, 24°17'E, Vesala et al., 2005), respectively. Parameters for two different street tree species (*Tilia* TA and *Alnus* AL) were derived in (Havu et al., 2022) from portable leaf gas exchange measurements from trees located on two streets in Helsinki, Finland (60°13'N, 25°0'E, Riikonen et al., 2011). Finally, appropriate parameters to be used for park trees (PK) were obtained from automated leaf-level chamber system on *Tilia* trees in a botanical garden in Helsinki (60°12'N, 24°57'E, Havu et al., 2024).

2.3.2 Parameters for grass and low vegetation

150 Three parameter sets were used to represent grass and low vegetation in the model simulations. Parameters for low vegetation (LV) representative for a mixture of meadows and lawns were based on EC observations made over a mixed vegetation type in a suburban area of Helsinki (60°12'N, 24°57'E, Järvi et al., 2019). In addition parameters for two different lawns using EC observations were derived in this study. First set of lawn parameters (La1) were derived using EC data from over an urban lawn in Espoo, within the western part of the Helsinki metropolitan region, Finland (60°11'N, 24°49'E, Havu et al., 2024). The
155 EC system was installed at a height of 1.2 m above ground level, positioned centrally within a 0.7 ha lawn area. The second set of lawn parameters (La2) representative for mid-latitude North American lawns was derived from EC data collected over an unirrigated turfgrass in the Minneapolis–Saint Paul metropolitan region in east-central Minnesota, US (44°59'N, 93°11'W, Peters et al., 2011). Measurements were taken 1.5 m above a 1.5 ha lawn. Details of the parameter fittings are found from Appendix C.



Table 2. Biogenic CO₂ model parameters for different vegetation types in the SUEWS model. See Eqs. 2, 3 and D1, and Appendix B for explanation for the parameters.

Parameters	Lawn 1 [La1]	Lawn 2 [La2]	Deciduous forest [DF]	Evergreen forest [EF]	Street tree (Tilia) [TA]	Street tree (Alnus) [AL]	Park tree [PK]	Low vegetation ^g [LV]
Biophysical								
$F_{photo,max}(\mu\text{mol m}^{-2} \text{s}^{-1} \text{ LAI}^{-1})$	5.22	6.53	9.9	7.0	8.35	13.18	9.2	12.4 ^a
a_{resp}	1.0	1.7	2.2	1.5	0.8	1.1	1.1	2.8
b_{resp}	0.11	0.06	0.05	0.06	0.08	0.08	0.03	0.05
$LAI_{max}(\text{m}^2 \text{m}^{-2})$	5.9	4.1	4.6	5.1	4.8	4.8	4.8	5.8
$LAI_{min}(\text{m}^2 \text{m}^{-2})$	1.6	1.6	1.0	4.0	1.0	1.0	1.0	1.0
Soil Properties & Surface Conductance								
$g_{max}(\text{mm s}^{-1})$	3.7	3.7	11.7 ^b / 2.9 ^c	7.4 ^b / 2.0 ^c	3.7	3.1	3.7	3.7
$G_1(\text{mm s}^{-1})$	3.5	3.5	3.5	3.5	3.5	3.5	3.5	3.5
$G_2(\text{W m}^{-2})$	232	264	474	366	477	475	458	566
G_3	0.54 ^d	0.54	0.001	0.00	0.66	0.80	0.57	0.24
G_4	0.87 ^d	0.87	0.98	0.95	0.90	0.80	0.75	0.44
$G_5(^{\circ}\text{C})$	30	30 ^e	30	30	30	30	30	30
$G_6(\text{mm}^{-1})$	1.48	0.55	0.1	0.1	0.36	0.08	0.74	0.05
$K_{L,max}(\text{W m}^{-2})$	1200	1200	1200	1200	1200	1200	1200	1200
$T_L(^{\circ}\text{C})$	-10	-10	-10	-10	-10	-10	-10	-10
$T_H(^{\circ}\text{C})$	55	55	55	55	55	55	55	55
Soil depth (cm)	30	10	45	40	100	100	34.9	35
Field capacity (%)	33 ^f	32 ^g	31 ^g	29 ^h	14	14	23	-
Wilting point (%)	16 ^f	24 ^g	5 ^g	10 ^h	6	6	10	-
$\Delta\theta_{WP}(\text{mm})$	43.6	23.7 (71.3) ^j	106.5 (236.7) ^j	50.9 (127.3) ^j	132.5	132.5	71.9 (206) ^j	120 (102.87) ^j
References	This study	This study	Havu et al. 2024	Havu et al. 2024	Havu et al. 2022	Havu et al. 2022	Havu et al. 2024	Järvi et al. 2019

^a Tréneau et al. 2024
^b Ward et al. 2016; values used for Swindon.
^c Breuer et al. 2003; values used for Minneapolis.
^d Adopted from Lawn 2
^e Fixed at 30^o C
^f Kätterer et al. 2006
^g Chen and Dudhia 2001
^h Kolari et al. 2022
ⁱ Scaled to 1 m
^j Scaled to 30 cm



160 2.4 Model setup and evaluation

In Swindon, SUEWS was run at an hourly temporal resolution for an area extending to a 500 m radius from the EC tower using the surface information from Table 1. Due to poor representation of LAI (mainly too early onset of leaf growth), coefficients describing its seasonal development were derived using satellite data from 2018–2022 (See Appendix D). Gap-filled hourly meteorological measurements were used to run the model for the study period from May 2011 to April 2013 when flux
165 observations were available for evaluation. A spin-up period from January to April 2011 was forced with the European Centre for Medium-Range Weather Forecasts (ECMWF) atmospheric reanalysis data (Hersbach et al., 2020) due to the lack of on-site observational data (in comparison Ward et al. (2016) used nearby observations). In Minneapolis, the same hourly temporal resolution was applied for the residential area (Fig. 1). Hourly meteorological data were collected on-site between July 2006 and April 2009 (Peters et al., 2011; Menzer and McFadden, 2017). These data were used to force the model for the study period
170 from May 2007 to April 2009, with a spin-up period from July 2006 to April 2007. Meteorological variability at the two study periods are shown in Figure 2.

In order to evaluate the sensitivity of SUEWS to surface conductance (G_1 – G_6), photosynthesis ($F_{pho,max,i}$), and respiration (a , b) parameters, 18 different parameter combinations were examined (Table E1). In these 18 cases, other model parameters were kept constant at both sites. We furthermore focused on a subset of cases to highlight differences between parameter
175 choices and to illustrate the uncertainty associated with the parameter selection. The subsets consisted of Cases 1, 3, 5, 9 and 12 for Swindon and Cases 1, 3, 5, 8 and 11 for Minneapolis (Table 3). The first three were the same between the two sites to demonstrate the impact of grass parameters on carbon exchange, while the other two cases were selected based on their good performance against EC measurements (Appendix E). The evaluation was made for summer months from May to August when the biogenic signal is its highest when compared to the anthropogenic emissions.

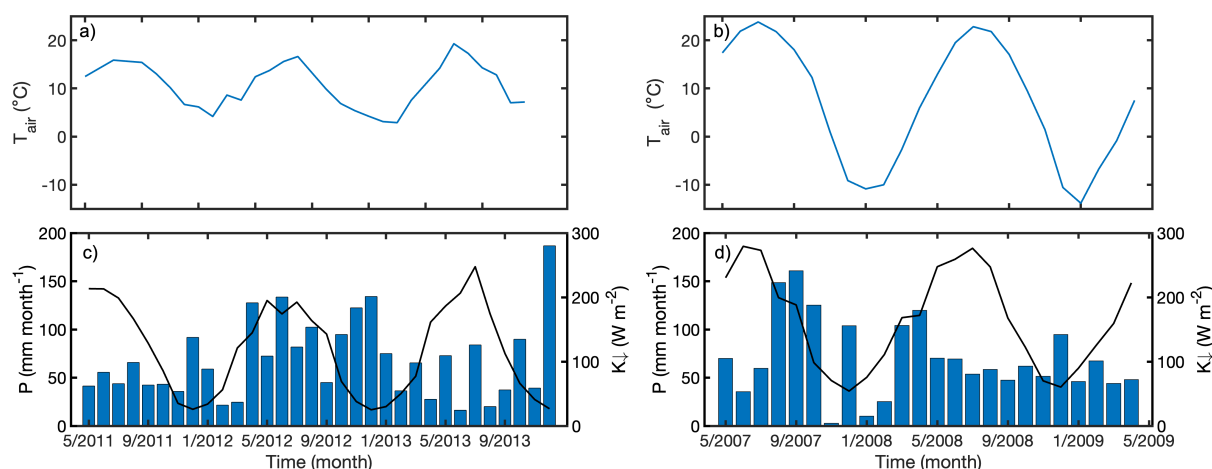


Figure 2. Monthly variability of air temperature (T , a-b), precipitation (P) and solar radiation (K) (c-d) during the study period in Swindon, UK (a,c) and Minneapolis, US (b,d).



Table 3. Summary of the five representative surface conductance parameter case combinations used to simulate photosynthesis and latent heat flux over Swindon and Minneapolis sites. The different cases use parametrisations derived from observations made over La1 = lawn in Helsinki, La2 = lawn in Minneapolis, LV = low vegetation, DF = deciduous forest, EF = evergreen forest, TA = street trees (Tilia). Conductance indicates the canopy-level responses of photosynthesis and evapotranspiration to environmental factors (Eq. 2) while the deciduous, evergreen and low vegetation are vegetation specific parameters.

Site	Swindon					Minneapolis				
Case	1	3	5	9	12	1	3	5	8	11
Conductance	La1	La1	La2	DF	TA	La1	La1	La2	DF	TA
Deciduous	DF	DF	DF	DF	TA	DF	DF	DF	DF	TA
Evergreen	EF	EF	EF	EF	EF	EF	EF	EF	EF	EF
Low vegetation	La1	LV	La2	LV	LV	La1	LV	La2	La2	La2

180 Model performances were assessed using standard statistical metrics of correlation coefficient (R), root-mean-square error (RMSE), and mean absolute error (MAE). The RMSE quantifies the average magnitude of model errors and was defined as:

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2}, \quad (4)$$

where y_i denotes the observed values and $\hat{y}_i$ the corresponding model predictions. The MAE, which indicates the average bias of the model, was calculated as:

$$185 \quad \text{MAE} = \frac{1}{n} \sum_{i=1}^n |y_i - x_i| \quad (5)$$

Furthermore, we use Taylor diagrams (Taylor, 2001) to visualize the model performance against the EC measurements.

3 Results and Discussion

3.1 Photosynthetic and respiration responses to environmental drivers

Figure 3 presents the environmental response functions for stomatal conductance (Eq. B2-B5), controlling photosynthesis and transpiration, and for respiration (Eq. 3) across the used datasets for various vegetation types (Table 2). In the surface conductance functions, a value of zero implies complete stomatal closure, meaning that transpiration and photosynthesis are fully inhibited by the respective environmental factor. Conversely, a value of one indicates no limitation, reflecting optimal conditions. For all vegetation types examined, the response function to incoming shortwave radiation $g(K \downarrow)$ exhibits minimal variability between the vegetation types. For lawns (La1 and La2), the stomata response to solar radiation is the most abrupt (smaller G_2) followed by the evergreen forest (EF) when compared to other tree types (DF, TA, AL, PK) and low vegetation (LV). A similar outcome was found by Omidvar et al. (2022) as based on observations from multiple natural ecosystems. The



similarity of the function forms suggests that selection of G_2 has a relatively small impact on the modelled photosynthesis and transpiration, at least in the studied ecosystems. This is consistent with previous findings reporting limited variation in radiation sensitivity of photosynthetic activity across various vegetation types, including those in urban environments (Bellucco et al., 2017). Temperature response functions $g(T_{\text{air}})$ overlap because the optimal temperature parameter (G_5), which defines the air temperature at where stomatal opening is maximal, was fixed at 30°C owing to the lack of observational data at sufficiently high temperatures. The used value agrees with the general understanding that stomatal conductance increases exponentially with temperature across the 15–35°C range in most plant species (Bunce, 2000; Urban et al., 2017).

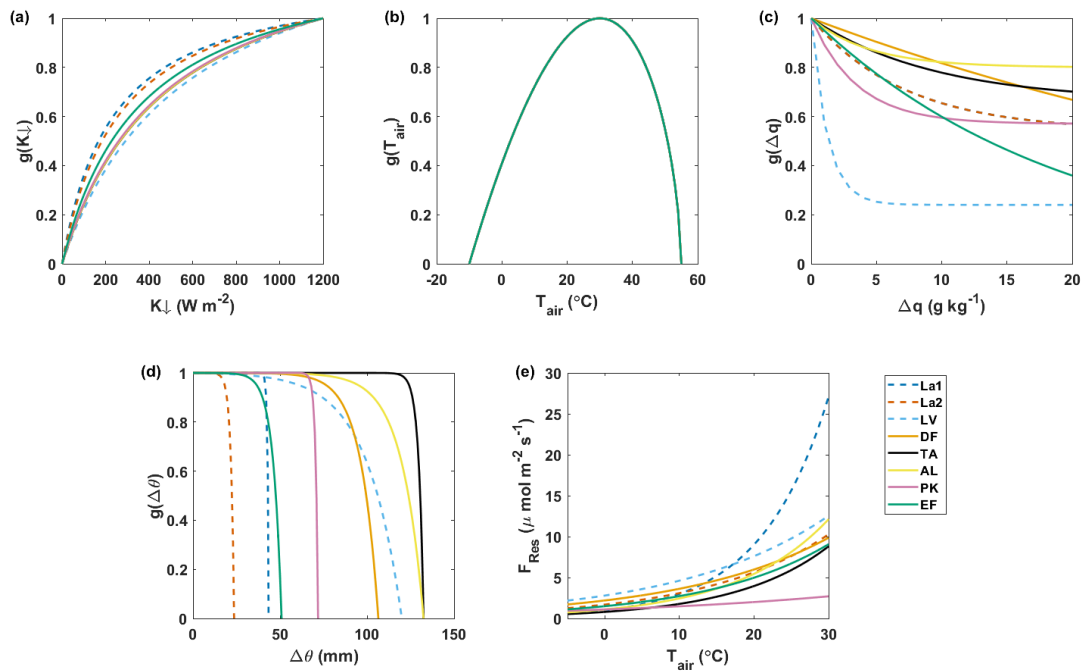


Figure 3. Environmental response functions for surface conductance (g , a–d), and soil and vegetation respiration (F_{res} , e) for different vegetation types (see Table 1 for site details): La1 = Lawn Helsinki, La2 = Lawn Minneapolis, LV = Low vegetation, DF = Deciduous broadleaf forest, TA = *Tilia* street trees, AL = *Alnus* street trees, PK = *Tilia* park trees and EF = Evergreen forest. The environmental variables influencing g are (a) incoming solar radiation ($K_{\downarrow}$), (b) air temperature (T_{air}), (c) specific humidity deficit (Δq), and (d) soil moisture deficit ($\Delta\theta$). Panel (e) shows the exponential relation of F_{res} with T_{air} . Note that the response functions for La1 and La2 overlap in panel (c).

In contrast, the specific humidity deficit response function $g(\Delta q)$ shows notable differences across vegetation types (Fig. 3c). This is consistent with the results from Chitsaz et al. (2024), which reported that many vegetation types respond strongly to atmospheric moisture compared to other environmental drivers. The tree vegetation types demonstrate a more gradual decline in stomatal response with increasing Δq , reflecting greater resistance to vapour pressure deficit than lawns and low vegetation, which have higher sensitivity to atmospheric moisture deficit. Large differences are also observed in the soil moisture deficit



response function $g(\Delta\theta)$. Stomatal opening in all vegetation types is highly sensitive to soil moisture deficits, often shutting
210 down abruptly in the model once a critical threshold (i.e. the wilting point) is reached. Notably, shorter vegetation types show
substantially lower tolerance to increasing soil dryness, while trees are able to maintain higher stomatal opening under drier
conditions. This observation is consistent with Chitsaz et al. (2024), which highlighted that soil moisture availability plays
a stronger limiting role for grasses compared to trees. Our results also align with Hoek van Dijke et al. (2023) and Zhang
et al. (2016), which show that trees and grass differ in their drought response strategies due to different physiological and
215 structural characteristics, especially in their stomatal regulation. The deeper rooting system of trees allows access to water
at deeper depths, including potential supplemental sources such as piped water systems in urban environments (Smith et al.,
2024; Shields and Tague, 2015).

Soil and vegetation respiration exhibits a large variability in temperature responses across the vegetation types. The lower
vegetation types La1, La2 and LV show stronger sensitivity with T_{air} than trees. This aligns with findings from Raich and
220 Tufekciogul (2000), which reported that, on average, grass has higher respiration rates than trees under comparable conditions.
In general, lawn respiration can be highly variable and strongly depends on the amount of soil organic material (Decina
et al., 2016; Bae and Ryu, 2017). A recent study in Helsinki found relatively little variations in soil and vegetation respiration
between irrigated and unirrigated lawns (Karvinen et al., 2024), whereas other studies observed clearly higher respiration
rates in irrigated lawns compared to unirrigated lawns (Trémeau et al., 2024). These contrasting results demonstrate the highly
225 complex nature of lawn respiration rates. Evergreen tree (EF) parameters provide a slightly lower soil and vegetation respiration
rate than deciduous tree (DF) parameters. The two datasets are based on data from two sites at different latitudes on different
continents, which can explain the differences. However, Huang et al. (2014) reported higher respiration from EF than from DF
due to differences in their root systems.

3.2 The impact of parameter selection on model performance

230 The tested 18 parameter configuration cases give a wide range of model performances when compared against the EC mea-
surements of net CO_2 at both in Swindon and Minneapolis during summer months from May to August (Appendix E). From
here onwards we focus on the selected five cases at both sites (Table 3). In Swindon, Cases 1 and 5 using the lawn parameters
for grass fail to capture the observed diurnal pattern of F_C (Fig. 4a–d) and CO_2 uptake is consistently underestimated. In
contrast, Cases 3, 9, and 12 with LV for grass show good agreement with observations, indicating that the LV parameterisa-
235 tion combining mixed vegetation type and meadow better represents grass photosynthesis at the site. This could be due to the
presence of undeveloped green corridors and grass verges alongside roads within the study area (Ward et al., 2013) or the low
vegetation simply does not follow the very steep decline with soil moisture in La1 and La2. The observed lowest F_C reaching
 $-3.0 \mu\text{mol m}^{-2} \text{s}^{-1}$ in daytime across all summer months is well captured by all three Cases using LV. Furthermore, Cases 9
and 12 using tree parameters for surface conductance perform slightly better than Case 3 (Table 4). Cases 9 and 12 have the
240 highest correlations ($R = 0.62\text{--}0.70$) and the lowest mean absolute errors ($\text{MAE} = 2.3\text{--}2.5 \mu\text{mol m}^{-2} \text{s}^{-1}$) when compared to
 $R = 0.17\text{--}0.48$ and $\text{MAE} = 2.8\text{--}4.1 \mu\text{mol m}^{-2} \text{s}^{-1}$ for Case 3. This demonstrates the importance of trees in controlling the
overall stomatal conductance at the Swindon site despite the surface fraction of trees being smaller (0.09) than grass (0.36).



Urban trees are more effective in taking up atmospheric CO₂ than other vegetation types (Thölix et al., 2025) and thus their stomatal control is more important for the overall uptake compared to grass or low vegetation. Taylor diagrams support these findings with negative relationship between observations and modelled values found with Cases 1 and 5 (Fig. 6a). In contrast, Cases 9 and 12 achieve strong positive correlations ($R = 0.68$ and 0.66 , respectively). Their standard deviations ($3.7\text{--}4.2 \mu\text{mol m}^{-2} \text{s}^{-1}$) are also closer to those of the observations. Large differences in the model performance in Swindon reflect the appropriate choice on vegetation parameters to be critical. Having the highest R and lowest standard deviations, Case 9 using low vegetation parameters for grass and deciduous forest parameters for surface conductance is the best case for the Swindon site.

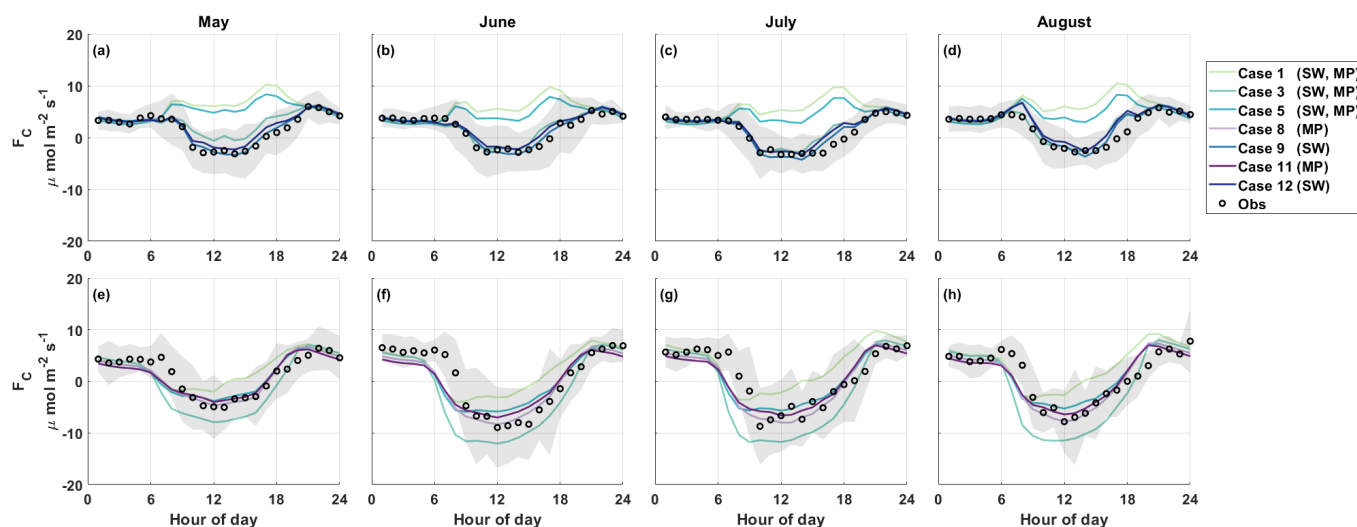


Figure 4. Median diurnal cycles of modelled versus observed hourly CO₂ flux (F_C , $\mu\text{mol m}^{-2} \text{s}^{-1}$) for (a–d) Swindon, UK and (e–h) Minneapolis, US over summer months from May to August. The shadowed areas show interquartile ranges of the observations.



Table 4. Comparison of model performance metrics for CO₂ flux (F_C , $\mu\text{mol m}^{-2} \text{s}^{-1}$) and latent heat flux (Q_E , W m^{-2}) of different cases during summer months from May to August at the Swindon and Minneapolis sites. Error metrics include the correlation coefficient (R), root mean square error (RMSE), and mean absolute error (MAE).

Swindon								Minneapolis							
Case	Month	F_C			Q_E			Case	Month	F_C			Q_E		
		R	RMSE	MAE	R	RMSE	MAE			R	RMSE	MAE	R	RMSE	MAE
1	May	-0.06	6.52	4.86	0.87	26.12	16.62	1	May	0.51	4.88	3.69	0.60	65.24	40.02
	Jun	-0.22	6.90	4.89	0.83	34.10	21.39		Jun	0.60	5.79	4.31	0.60	83.80	54.54
	Jul	-0.26	7.93	5.67	0.78	37.48	24.29		Jul	0.49	6.44	5.04	0.67	74.27	50.16
	Aug	-0.10	6.32	4.61	0.88	28.99	18.10		Aug	0.50	6.65	5.10	0.63	75.61	47.65
3	May	0.44	4.65	3.15	0.85	27.56	17.60	3	May	0.64	5.04	3.79	0.60	65.24	40.02
	Jun	0.17	5.77	3.75	0.81	35.56	22.21		Jun	0.72	6.83	4.85	0.60	83.80	54.54
	Jul	0.17	6.50	4.13	0.77	38.75	25.02		Jul	0.66	7.04	4.96	0.67	74.27	50.16
	Aug	0.48	4.11	2.75	0.88	29.34	18.28		Aug	0.65	7.04	5.32	0.63	75.61	47.65
5	May	0.08	5.83	4.31	0.86	27.00	17.33	5	May	0.60	4.30	3.26	0.63	64.35	39.15
	Jun	-0.10	6.02	4.17	0.84	33.79	21.56		Jun	0.70	5.14	3.76	0.62	83.65	54.37
	Jul	-0.15	6.84	4.77	0.79	37.61	24.60		Jul	0.63	5.25	3.79	0.70	74.76	50.50
	Aug	0.10	5.10	3.70	0.89	29.36	18.41		Aug	0.68	5.29	3.81	0.66	78.30	49.83
9	May	0.68	3.36	2.44	0.88	23.96	15.32	8	May	0.63	4.27	3.24	0.65	64.63	39.13
	Jun	0.64	3.47	2.49	0.90	25.51	17.06		Jun	0.74	5.00	3.58	0.65	84.31	54.69
	Jul	0.70	3.28	2.44	0.85	28.82	18.88		Jul	0.68	5.11	3.68	0.72	76.04	51.43
	Aug	0.65	3.22	2.34	0.86	34.13	22.23		Aug	0.67	5.19	3.67	0.67	79.07	50.55
12	May	0.66	3.35	2.43	0.88	27.19	17.65	11	May	0.61	4.23	3.22	0.65	64.95	39.37
	Jun	0.62	3.36	2.40	0.90	32.65	22.40		Jun	0.73	4.98	3.67	0.65	84.57	54.93
	Jul	0.67	3.27	2.41	0.85	31.92	20.94		Jul	0.67	5.00	3.66	0.72	76.58	51.91
	Aug	0.64	3.22	2.34	0.86	34.13	22.23		Aug	0.67	5.19	3.67	0.67	79.07	50.55

The subset of cases simulate F_C in Minneapolis better than in Swindon, although the level of agreement varies between cases and months (Figs. 4 and 6 a–b). Cases 1 and 3 using surface conductance and grass parameters from La1 or LV do not simulate the observed F_C well with Case 1 underestimating and Case 3 overestimating the measured flux. In contrast, Cases 5, 8, and 11 using La2 for grass photosynthesis and respiration, show much better agreement, with minimum F_C ranging from approximately -4.8 to $-10.3 \mu\text{mol m}^{-2} \text{s}^{-1}$ in daytime when compared to the observed values of -5.1 – $9.0 \mu\text{mol m}^{-2} \text{s}^{-1}$. These cases have high correlations ($R = 0.60$ – 0.74) and lower mean absolute errors ($\text{MAE} = 3.2$ – $3.8 \mu\text{mol m}^{-2} \text{s}^{-1}$) (Table 4). The better performance of La2 when compared to La1 and LV is reasonable as its parameters are based on observations collected over urban lawn within the source area of the EC tower in Minneapolis (Peters and McFadden, 2012). Similarly to Swindon, surface conductance of trees (Cases 8 and 11) give slightly better model performance ($R = 0.61$ – 0.74 and $\text{MAE} = 3.2$ – $3.7 \mu\text{mol m}^{-2} \text{s}^{-1}$) than La2 ($R = 0.60$ – 0.70 and $\text{MAE} = 3.2$ – $3.8 \mu\text{mol m}^{-2} \text{s}^{-1}$). In Taylor diagrams (Figs. 6 a–b), correlation coefficients of the different cases range from 0.55 (Case 1) to 0.69 (Case 8), indicating that the model captures the observed F_C well. Apart from Case 5, which exhibits a slightly larger standard deviation ($7.7 \mu\text{mol m}^{-2} \text{s}^{-1}$), the remaining cases show a narrow range in variability (4.9 – $5.6 \mu\text{mol m}^{-2} \text{s}^{-1}$). Case 8 achieves the highest correlation and Case 11 the lowest variability ($4.9 \mu\text{mol m}^{-2} \text{s}^{-1}$). Case 8 using La2 for grass specific parameters and DF for canopy level surface conductance parameters consistently shows slightly better agreement with observations and can therefore be regarded as the optimal case for the Minneapolis site.

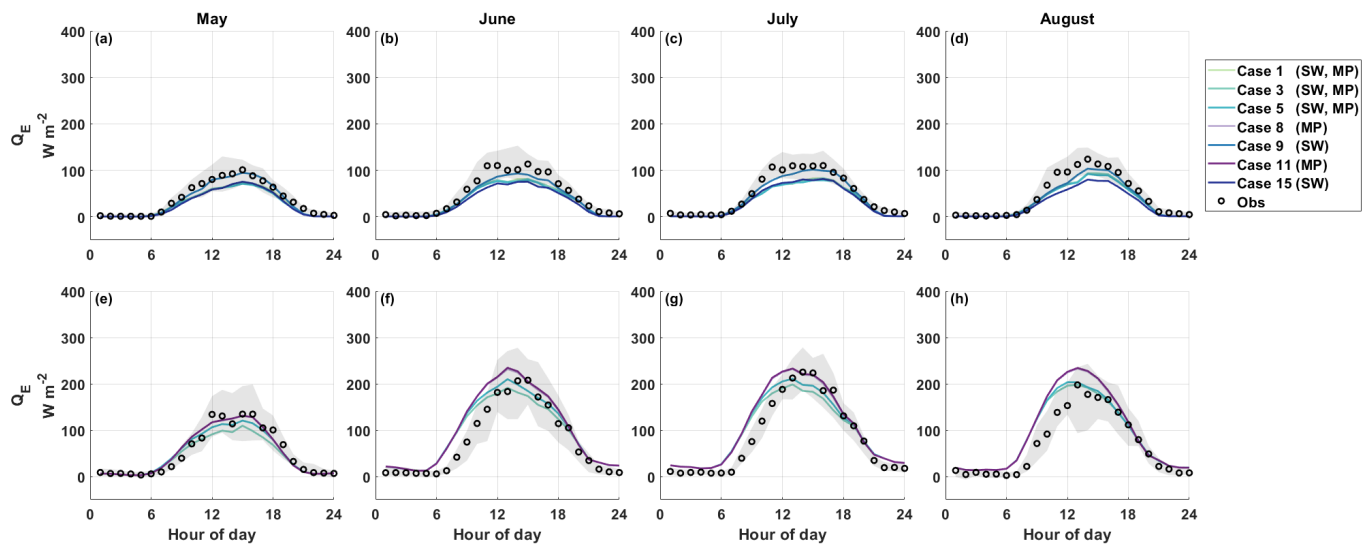


Figure 5. Median diurnal cycles of modelled and observed latent heat flux (Q_E , W m^{-2}) for (a–d) Swindon, UK and (e–h) Minneapolis, US during summer months from May to August. Shaded areas show the interquartile range of the measurements.

The different parameter have smaller impact on Q_E than in F_C (Fig. 5) due to the less direct effect of stomatal control on transpiration in the model equations (Järvi et al., 2011). In Swindon, the cases using DF for canopy-level surface conductance and LV for grass specific parameters provide the best model performances over the other cases (Table 4, Fig. 6). Out of these, Case 9 creates slightly lower MAE ($15.3\text{--}22.2 \text{ W m}^{-2}$) when compared to Case 12 ($17.7\text{--}22.4 \text{ W m}^{-2}$) being thus consistent of being the best case in Swindon. Similarly, in Minneapolis the cases using La2 for grass and DF for surface conductance provide the best simulated Q_E with MAE $39.1\text{--}54.7 \text{ W m}^{-2}$ when compared to the other cases with $39.4\text{--}54.9 \text{ W m}^{-2}$.

In Minneapolis, the model performance is less sensitive to variations in vegetation parameters compared to Swindon where larger differences among the studied cases are seen. The large variation in Swindon is due to the lawn parameters which were not able to simulate grass photosynthesis and respiration well. The ground vegetation in Swindon is more heterogenous than in Minneapolis, where lawns are the main ground vegetation type.

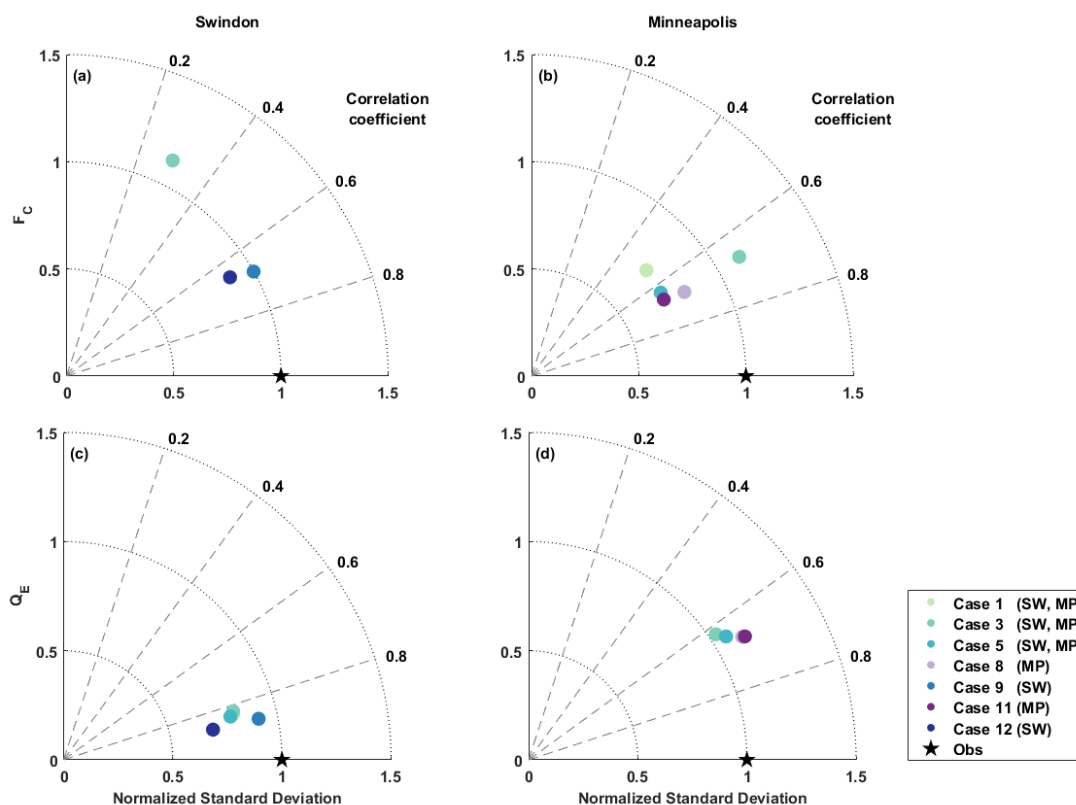


Figure 6. Taylor diagrams comparing modelled total carbon flux (F_C , a–b) and latent heat flux (Q_E , c–d) against observations for Swindon (a, c) and Minneapolis (b, d). Each point represents a different model case, with radial distance denoting the standard deviation normalized by the observations (Obs) and the angular axis the correlation coefficient (R). Case 9 is identified as the optimal model configuration for Swindon, and Case 8 for Minneapolis. Note that Cases 1 and 5 for F_C in Swindon are excluded due to negative R .

3.3 Modelled cumulative biogenic F_C

The selection of the vegetation parameters significantly influences the cumulative biogenic carbon flux (F_{bio} , Fig. 7). In Swindon, photosynthetic carbon uptake (F_{pho}) varies from $-95 \text{ g C m}^{-2} \text{ month}^{-1}$ in May (Case 1) to $-233 \text{ g C m}^{-2} \text{ month}^{-1}$ in July (Case 9) (Fig. 7a). Cases 1 and 5 consistently show the lowest F_{pho} while Case 9 exhibits the largest values. This suggests that the grass conductances La1 and La2 simulate lower CO_2 assimilation under the same environmental conditions when compared to other cases. Vegetation and soil respiration (F_{res}) shows less variability, with values ranging from $64 \text{ g C m}^{-2} \text{ month}^{-1}$ in May (Case 5) to $103 \text{ g C m}^{-2} \text{ month}^{-1}$ in August (Case 1). Most cases give negative F_{bio} ranging from -20 to $-95 \text{ g C m}^{-2} \text{ month}^{-1}$, indicating a net carbon sink. The only exceptions are Case 1 in July and August, which show a small net carbon source of $4.7\text{--}5.9 \text{ g C m}^{-2} \text{ month}^{-1}$. Following the trends in F_{pho} , Cases 1 and 5 consistently exhibit lower net carbon uptake (approximately 40–50% less than other cases across all months). In contrast, Cases 3, 9, and 12, using LV as the



grass conductance, display similar, more effective CO_2 uptake. For Cases 9 and 12, the use of tree surface conductances (DF and TA) instead of LV gives slightly higher carbon sinks. F_{bio} is thus more controlled by F_{pho} rather than soil and vegetation respiration on these summer months.

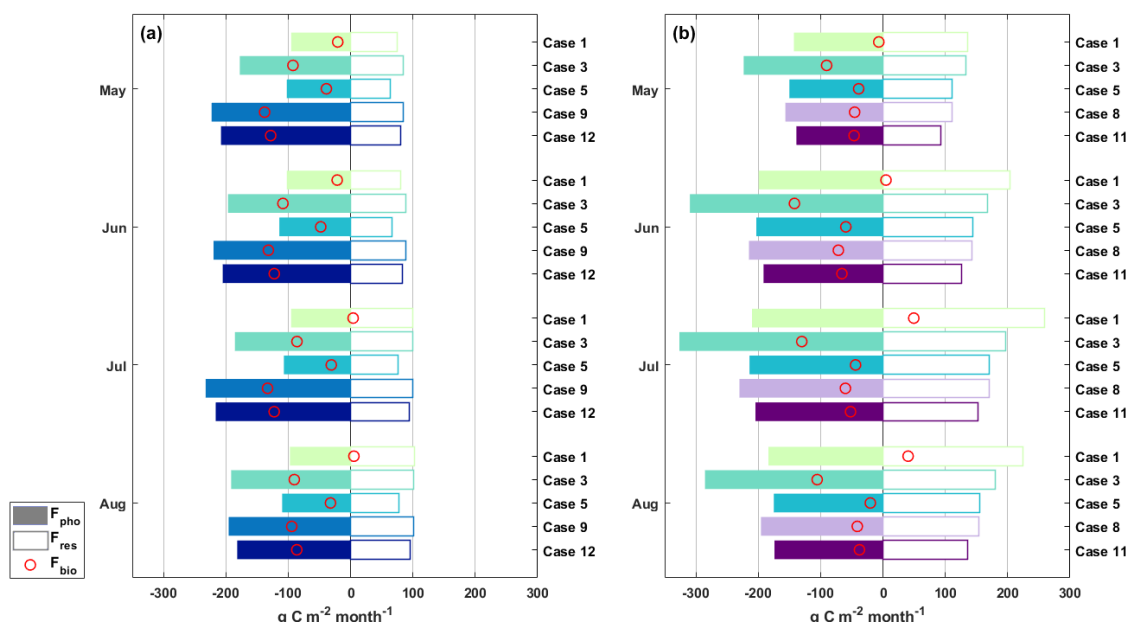


Figure 7. Modelled cumulative biogenic flux F_{bio} components in summer months (May–August) for the five selected cases in (a) Swindon, UK and (b) Minneapolis, US. Bars show modelled photosynthetic uptake (F_{pho} , solid filled) and respiration (F_{res} , white-filled with colored edges). Red circles indicate total F_{bio} .

290 The modelled biogenic fluxes are larger in Minneapolis (Fig. 7b) than in Swindon. F_{pho} range from $-139 \text{ g C m}^{-2} \text{ month}^{-1}$ in May (Case 11) to $-327 \text{ g C m}^{-2} \text{ month}^{-1}$ (Case 3) in July, while F_{res} varies from 92 to $260 \text{ g C m}^{-2} \text{ month}^{-1}$, resulting in substantially more negative F_{bio} than in Swindon. The trees are larger and the vegetation fraction is higher in Minneapolis than in Swindon but also air temperature and solar radiation are higher indicating more optimal stomatal conductance conditions. Most cases indicate a net carbon sink (-6.7 to $-141.9 \text{ g C m}^{-2} \text{ month}^{-1}$), with the exception of Case 1 which gives a net carbon source of 4.8 – $49.4 \text{ g C m}^{-2} \text{ month}^{-1}$ from June to July. Cases 1, 5, 8, and 11 produce similar F_{pho} throughout the growing season, suggesting that the La1 and La2 grass conductances have only a minor impact in photosynthetic uptake under these environmental conditions. However, La1 consistently results in higher respiration, contributing to smaller net carbon sink (F_{bio}). In contrast, Case 3 with LV grass conductance, produces substantially stronger photosynthetic uptake—approximately 50% higher than the other cases—indicating a greater capacity for CO_2 assimilation under identical conditions. The large differences in monthly cumulative F_{bio} among the cases highlight the importance of selecting appropriate vegetation parameters for accurately simulating biogenic fluxes. Poor parameter selection can lead to modelled emissions when, in reality, an uptake

295

300



occurs. The modelled differences using different parameter selections at each site are larger than those reported for Helsinki and Zurich using different models: Thölix et al. (2025) found an annual difference of approximately $50 \text{ g C m}^{-2} \text{ yr}^{-1}$ between two land surface models for an urban park in Helsinki while Stagakis et al. (2025) reported an annual difference of $680 \text{ g C m}^{-2} \text{ yr}^{-1}$ between remote sensing and process-based models.

3.4 Annual net carbon balance with different parameter selections

The total annual carbon fluxes (F_C , Fig. 8) further illustrate the sensitivity of carbon exchange to the choice of conductance and biogenic parameters. In Swindon, annual F_C varies from approximately 2.2 to $2.8 \text{ kg C m}^{-2} \text{ yr}^{-1}$ in Year 1 and from approximately 2.4 to $2.9 \text{ kg C m}^{-2} \text{ yr}^{-1}$ in Year 2, with Case 1 consistently producing the highest net carbon emissions.

Cases with strongest photosynthetic uptake (Cases 9 and 12) using LV for grass and trees as overall surface conductance, give approximately 15–20% lower F_C than the other cases. As reported in Ward et al. (2015), the observed annual F_C at Swindon was $1.75 \text{ kg C m}^{-2} \text{ yr}^{-1}$, about 21% lower than the model's optimal configuration ($2.2 \text{ kg C m}^{-2} \text{ yr}^{-1}$, Case 9). This indicates that although the model reproduces observed fluxes well during the summer months, it tends to overestimate F_C in winter. In Swindon, some of the vegetation remains green also over winter months. In Minneapolis, the impact of vegetation parameters is even more pronounced. Annual F_C varies from approximately 1.0 to $1.7 \text{ kg C m}^{-2} \text{ yr}^{-1}$ in Year 1 and from approximately 0.9 to $1.5 \text{ kg C m}^{-2} \text{ yr}^{-1}$ in Year 2. Case 1 produces the highest annual F_C , whereas Case 3 (LV as grass conductance) produces lower than the other cases. Menzer and McFadden (2017) reported an observed annual F_C of approximately $1600 \text{ g C m}^{-2} \text{ yr}^{-1}$, being 20% higher than the optimal model simulation (Case 8) $1.3 \text{ kg C m}^{-2} \text{ yr}^{-1}$. The differences between the modelled and observed annual sums are larger than seen in Helsinki where differences up to 3% were seen between modelled and observed values (Järvi et al., 2019). In Helsinki, mostly district heating is used which makes the simulation more straightforward as no information on building heating is needed. On the other hand, the differences are close to deviations seen in Beijing (around 15%).

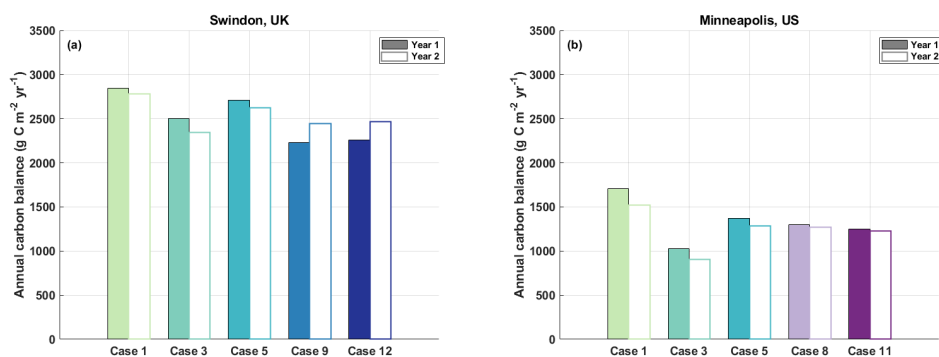


Figure 8. Modelled cumulative annual total carbon fluxes for the five cases in (a) Swindon, UK (Year 1 from May 2011 to April 2012, and Year 2 from May 2012 to April 2013), and (b) Minneapolis, US (Year 1 from May 2007 to April 2008, and Year 2 from May 2008 to April 2009).



The optimal configurations (Case 9 in Swindon and Case 8 in Minneapolis) produce modelled values (2.2 and $1.3 \text{ kg C m}^{-2} \text{ yr}^{-1}$, respectively) broadly consistent with observations reported in other suburban areas such as Melbourne (Coutts et al., 2007), Helsinki (Järvi et al., 2012), Montreal (Bergeron and Strachan, 2011) and Baltimore (Crawford et al., 2011), where annual F_C values are 2.32 , 1.76 , 1.36 and $0.36 \text{ kg C m}^{-2} \text{ yr}^{-1}$, respectively. These results demonstrate that the parameters selection on surface conductance and photosynthesis produce a substantial influence on long-term urban carbon budgets, even when biogenic fluxes comprise a relatively small component of the total F_C .

3.5 Seasonal variation in CO_2 balance at the two sites

The modelled net carbon flux (F_C) using the best vegetation parameterisation cases (Case 9 in Swindon, Case 8 in Minneapolis) show a clear seasonal cycle at both sites (Fig. 9). Swindon remains a net CO_2 source throughout the year, while Minneapolis exhibits a weak net sink in summer. In Swindon, minimum F_C of $42 \text{ g C m}^{-2} \text{ month}^{-1}$ is reached in July, corresponding to the peak photosynthetic uptake ($F_{pho} = -233 \text{ g C m}^{-2} \text{ month}^{-1}$). The biogenic uptake is not able to compensate for traffic ($136\text{--}142 \text{ g C m}^{-2} \text{ month}^{-1}$) and building emissions ($22\text{--}52 \text{ g C m}^{-2} \text{ month}^{-1}$). This is consistent with EC observations which show the Swindon site to act as a net CO_2 source in all seasons despite net uptake taking place during daytime in the summer (Ward et al., 2013). In fall, F_{pho} decreases indicating end of the growing season, and the site transitions into a large source, with the net CO_2 fluxes reaching $310 \text{ g C m}^{-2} \text{ month}^{-1}$ in December and January. In summer, photosynthesis and traffic dominate the carbon balance at the site while in winter, both building and traffic emissions are high. In Minneapolis the biogenic net uptake exceeds the emissions in June and August, resulting in a net sink of $-21.2 \text{ g C m}^{-2} \text{ month}^{-1}$ and $-9.6 \text{ g C m}^{-2} \text{ month}^{-1}$, respectively. In winter, the net CO_2 fluxes reach $157 \text{ g C m}^{-2} \text{ month}^{-1}$ in January with building emissions contributing the largest emissions. At both sites the different modelled components follow those partitioned from the EC observations using different bottom-up approaches (Ward et al., 2013, 2015; Menzer and McFadden, 2017).

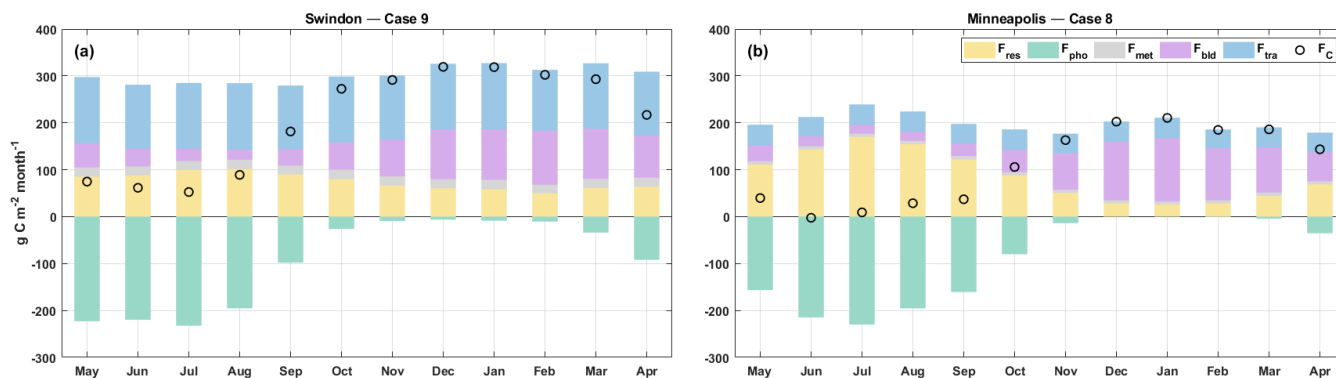


Figure 9. Monthly modelled cumulative carbon flux and its components in (a) Swindon, UK and (b) Minneapolis, US averaged over two years using the best vegetation parametrisations (Case 9 and Case 8, respectively). The coloured bars are contributions from traffic F_{tra} (blue), building emissions F_{bld} (purple), metabolism F_{met} (gray), photosynthesis F_{pho} (green), and respiration F_{res} (yellow). Black circles denote the net flux F_C , corresponding to the sum of all components.



Examining the different carbon balance components in detail shows how Swindon has three times larger traffic emissions (136–142 g C m⁻² month⁻¹) than Minneapolis (40–44 g C m⁻² month⁻¹). This creates a substantially higher baseline emis-
345 sion that prevents the site from becoming a net carbon sink even on summer months. At both sites building emissions originating from natural gas combustion for space and water heating are high over winter months (74 g C m⁻² month⁻¹ in Minneapolis and 115 g C m⁻² month⁻¹ in Swindon) but in Minneapolis these fall below 11 g C m⁻² month⁻¹ during summer. The larger building emissions in summer can be due to the colder temperatures and/or larger need for water heating. Human metabolic emissions remain low at both sites (less than 10 g C m⁻² month⁻¹) throughout the year, reflecting the relatively low population
350 density at both sites. In more dense neighbourhoods, human metabolism can be a significant contributor to the net CO₂ emissions. In Zurich, Switzerland, human metabolism has been found to cover 13% of the city's anthropogenic emissions (Brunner et al., 2025), while in central Helsinki this fraction was over 60% due to missing local level emissions in the district heating dominated area (Järvi et al., 2019). F_{res} increases in summer at both sites in relation to the higher air temperatures (Fig. 2). In Minneapolis, the relationship with temperature is steeper than in Swindon due to the differences in the parameters describing
355 vegetation and soil respiration (Fig. 3e). In Swindon some F_{pho} prevails throughout the winter months as the monthly air temperatures remain above freezing whereas in Minneapolis monthly temperatures drop below -10 °C preventing photosynthesis to take place. Wintertime uptake has also been seen in Indianapolis, US, over managed turfgrass despite the lower temperatures and radiation levels (Horne et al., 2025).

3.6 Estimation of anthropogenic emissions from flux partitioning

360 One of the main reasons for the need to simulate biogenic carbon exchange F_{bio} in cities is to separate the biogenic components from the net CO₂ flux in order to quantify the anthropogenic emissions F_{ant} . To examine the performance of SUEWS in flux partitioning we calculated observed F_{ant} by subtracting modelled F_{bio} from observed F_C during summer months from May to August and compare this with modelled F_{ant} . In Swindon, the modelled and observed F_{ant} show a similar behaviour (Fig. 10a). The morning and afternoon peaks (07:00–08:00 and 15:00–16:00) are well captured, with the modelled afternoon
365 median of 12.6 μmol m⁻² s⁻¹ closely matching the observed median of 10.9 μmol m⁻² s⁻¹. Nighttime emissions also show good agreement indicating that the model effectively captures the temporal profiles of traffic and building emissions. In Minneapolis (Fig. 10b), the modelled F_{ant} reproduces the observed F_{ant} less accurately, showing lower agreement and greater variability relative to Swindon. Particularly, the observed morning peak (07:00–08:00) is pronounced when compared to the modelled F_{ant} (observed: 8.1 μmol m⁻² s⁻¹; modelled: 3.1 μmol m⁻² s⁻¹). The afternoon peak, on the other hand,
370 is similarly captured by both observations and modelling (observed: 4.2 μmol m⁻² s⁻¹; modelled: 4.6 μmol m⁻² s⁻¹). The morning rush hour is concentrated into a narrow time window whereas in the afternoon, traffic is more spread both in space and time. These deviations reflect also high spatial heterogeneity in traffic emissions causing mismatch with source and model areas. Most of the traffic emissions at the site originate from the main roads and, with appropriate wind direction (Menzer et al., 2015), the traffic emission signal will be high. SUEWS on the other hand simulates emissions from the whole area and thus
375 the morning peak is smaller.



Nevertheless, the analysis shows how two independent estimates of F_{ant} , one from bottom-up emission modelling and one from flux partitioning, match well at the two sites, showing the capability of an urban land surface model in predicting well the biogenic flux components.

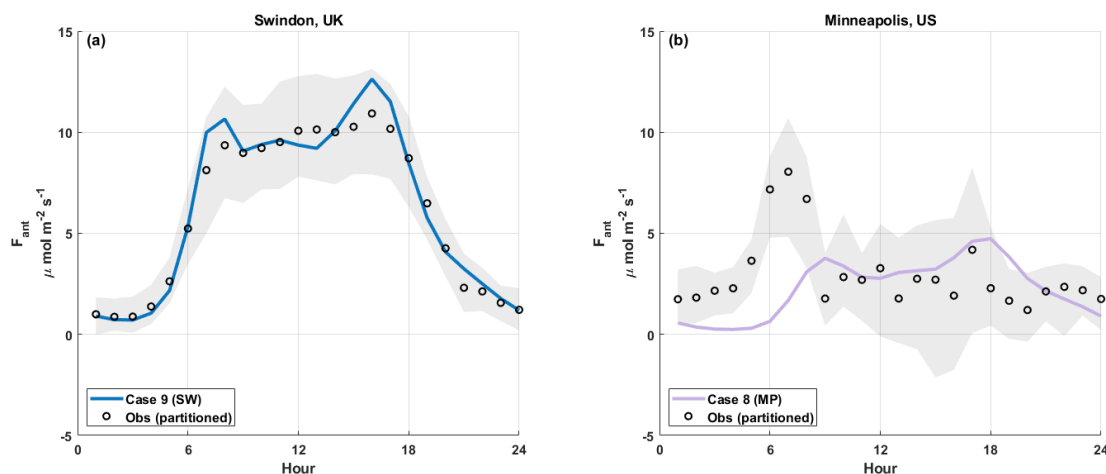


Figure 10. Average diurnal profiles of anthropogenic CO₂ fluxes F_{ant} in (a) Swindon, UK and (b) Minneapolis, US during the summer months (May–August). Colored lines represent the median of modelled anthropogenic fluxes using optimal configurations (Case 9 for Swindon and Case 8 for Minneapolis), with the shaded area indicating the interquartile range of the observations. Black circles denote the partitioned observed anthropogenic components (Obs), derived by subtracting modelled biogenic fluxes F_{bio} from observed total CO₂ fluxes F_C .

4 Conclusions

380 The main aim of this study was to examine the effect of surface conductance, photosynthesis and soil and vegetation respiration parameters on modelled CO₂ and latent heat fluxes, and to evaluate the model performance against urban EC measurements in mid-latitude suburban neighbourhoods in Swindon (UK) and Minneapolis (US). For this, the study combines a comprehensive set of parameters derived from EC and chamber measurements made in different urban and natural vegetation types.

The differences in surface conductance, maximum photosynthesis, and soil and vegetation parameters across vegetation
385 types are pronounced, with lower vegetation types generally exhibiting greater sensitivity to factors such as soil moisture than trees. In general, surface conductance parameters are most sensitive to soil moisture and specific humidity compared to radiation or air temperature. Therefore, particular attention should be paid to the selection of these parameters when applying SUEWS at new sites, while careful consideration should also be given to the parameters describing vegetation and soil respiration in the model. CO₂ fluxes are more sensitive to the parameter selection than the latent heat fluxes. At both Swindon and
390 Minneapolis sites, the best model performance is obtained using canopy-level surface conductance parametrisations from trees



($R = 0.62$ – 0.70 in Swindon, $R = 0.61$ – 0.74 in Minneapolis) rather than from lawns and low vegetation ($R \leq 0.48$ in Swindon, $R \leq 0.70$ in Minneapolis) even though the surface cover of trees would be smaller highlighting the role of trees in controlling stomatal control. Appropriate selection of surface conductance and photosynthesis is critical for accurately simulating net biogenic CO_2 uptake and its components—photosynthesis, vegetation and soil respiration—during the summer months, as well as for assessing annual balances of net CO_2 exchange including both anthropogenic emissions and biogenic components. Carbon balances between the two neighbourhoods vary depending on traffic intensity, building heating, photosynthesis, and soil respiration.

In broader terms, the choice of parameters for different vegetation types is critical for the performance of SUEWS. This also highlights the need for more observations of urban vegetation to improve the parametrisation of urban vegetation and soils. Using parameters derived from non-urban vegetation or from an inappropriate vegetation type as a reference can lead to substantial errors in the estimation of biogenic carbon exchange.



Appendix A: Anthropogenic CO₂ components

The components F_M and F_V of anthropogenic CO₂ flux (F_{ant}) are estimated with an inventory approach using population density, traffic rate, and their emission factors (EFs, Järvi et al., 2019). The hourly CO₂ emissions from human metabolism on workdays and weekends ($F_{M,h,d}$, $\mu\text{mol m}^{-2} \text{s}^{-1}$) are calculated using:

$$F_{M,h,d} = p_{h,d} \cdot H_{a,h,d} \cdot C_M, \quad (\text{A1})$$

where $p_{h,d}$ is the population density (cap ha^{-1}), $H_{a,h,d}$ activity by hour calculated from the diurnal profiles for population and activity, and C_M CO₂ released per person ($\mu\text{mol CO}_2 \text{s}^{-1} \text{cap}^{-1}$). The hourly traffic CO₂ emissions ($F_{V,h,d}$) on weekdays or weekends are calculated from

$$F_{V,h,d} = Tr_d \cdot E_{c,d} \cdot H_{T,d}, \quad (\text{A2})$$

where Tr_d is the mean daily traffic rate within the study area ($\text{veh day}^{-1} \text{area}^{-1}$), $H_{T,d}$ diurnal traffic profiles, and $E_{c,d}$ traffic EFs for CO₂ ($\text{kg km}^{-1} \text{veh}^{-1}$). Hourly building CO₂ emissions ($F_{B,h,d}$) on weekdays or weekends are calculated from

$$F_{B,h,d} = [f_{r_{heat}} \cdot (Q_{F,heat} + Q_{F,cool}) + f_{r_{nonheat}} \cdot Q_{F,base} \cdot f_{r_{QF,base,BEU,d}}] \cdot E_{CO2perJ}, \quad (\text{A3})$$

where $Q_{F,heat}$ and $Q_{F,cool}$ are building heating and cooling related emission and $Q_{F,base}$ is the non-temperature related anthropogenic heat flux (W m^{-2}) on weekdays or weekends (d) estimated from heating degree day model (Järvi et al., 2011):

$$Q_{F,d} = Q_{F,base} + Q_{F,cool} + Q_{F,heat} = p_{h,d} [a_{0,d} + a_{1,d} \text{CDD} + a_{2,d} \text{HDD}]. \quad (\text{A4})$$

$f_{r_{heat}}$ is the fraction of fossil fuels used for heating, $f_{r_{nonheat}}$ fraction of fossil fuels used for energy other than heating (e.g. combustion from domestic cooking), $f_{r_{QF,base,BEU,d}}$ the fraction of the $Q_{F,base}$ coming from building energy use, $E_{CO2perJ}$ is the EF for fuels in building energy use. Tables 1 and A1 summarise the anthropogenic parameter values used for the two sites.

Table A1. Parameter values used to calculate the anthropogenic carbon emissions.

Parameter	Swindon	Minneapolis
$C_{M(min)}$ ($\mu\text{mol CO}_2 \text{s}^{-1} \text{cap}^{-1}$)	120	120
$C_{M(max)}$ ($\mu\text{mol CO}_2 \text{s}^{-1} \text{cap}^{-1}$)	280	280
$E_{c,d}$ ($\text{kg km}^{-1} \text{veh}^{-1}$)	0.2069	0.7870
$f_{r_{heat}}$	0.7	1
$f_{r_{nonheat}}$	0	0.2
$f_{r_{QF,base,BEU,wd}}$	0.5096	0.7991
$f_{r_{QF,base,BEU,we}}$	0.5429	0.8204
$E_{CO2perJ}$	1.1590	1.1590
$a_{0,d}$	0.3081	0.3081
$a_{1,d}$	0.0099	0.0099
$a_{2,d}$	0.0102	0.0102



Appendix B: Biogenic CO₂ components

The environmental response functions $g(T_{air})$, $g(\Delta q)$, $g(\Delta\theta)$, and $g(K_{\downarrow})$ for air temperature, specific humidity deficit, soil moisture deficit, and shortwave radiation, respectively, are represented with the functional forms (Ward et al., 2016)

$$g(K_{\downarrow}) = \frac{K_{\downarrow}/(G_2 + K_{\downarrow})}{K_{\downarrow,max}/(G_2 + K_{\downarrow,max})}, \quad (B1)$$

$$425 \quad g(\Delta q) = G_3 + (1 - G_3)G_4^{\Delta q}, \quad (B2)$$

$$g(T_{air}) = \frac{(T_{air} - T_L)(T_H - T_{air})^{T_C}}{(G_5 - T_L)(T_H - G_5)^{T_C}}, \quad (B3)$$

and

$$430 \quad g(\Delta\theta) = \frac{1 - \exp(G_6(\Delta\theta - \Delta\theta_{WP}))}{1 - \exp(-G_6\Delta\theta_{WP})}, \quad (B4)$$

where

$$T_C = \frac{(T_H - G_5)}{(G_5 - T_L)}. \quad (B5)$$

The conductance parameters G_2 to G_6 characterize how stomatal conductance responds to environmental factors. T_H and T_L (°C) represent the upper and lower temperature thresholds where photosynthesis and transpiration are "switched off". $K_{\downarrow,max}$ (W m⁻²) denotes the maximum recorded shortwave radiation and $\Delta\theta_{WP}$ (mm) denotes the wilting point deficit.

Appendix C: Lawn parameter fitting

Eddy covariance (EC) data from the urban lawns in Espoo (La1) and Minneapolis (La2) were used to derive $F_{pho,max,grass}$ and G_2 – G_6 in Eqs. 2 and B1–B4, and a_{grass} and b_{grass} in Eq. 3. In Havu et al. (2024) data from La1 was used to fit the environmental control parameters G_2 – G_6 for lawns, but here refitting is made to get also $F_{pho,max,grass}$. To fit the soil and vegetation respiration parameters only nocturnal data ($K_{\downarrow}=0$) were used.

For the fitting process of photosynthesis, the observed photosynthesis at each site was calculated by subtracting nighttime respiration from the measured net ecosystem exchange (NEE) as the dependent variable; conversely, the observed values of T_{air} , $K_{\downarrow}$, Δq and soil water content (SWC) were used as independent variables. The photosynthesis fitting was conducted under the conditions of $K_{\downarrow}$ and Δq exceeding 10 W m⁻² and 1 g kg⁻¹, respectively. These thresholds were set to ensure that stomatal conductance values are representative, as lower values may cause deviations in stomatal behavior, potentially leading to inaccurate parameter estimation (Bosveld and Bouten, 2001). The bootstrapping method was used for the fitting, consisting of 100 iterations where seven-eighths of the available observations were randomly selected for each iteration. The selected data subsets were then fitted using non-linear regression via the least-squares method. The potential photosynthesis and surface conductance parameters (Eq. 2) were then determined by calculating the medians of the bootstrapped fits. The full set of parameters used in the model simulation are summarized in Table 1.



Appendix D: Seasonal dynamics of LAI

In SUEWS, the seasonal development of LAI is described as (Zheng et al., 2023)

$$LAI_{d,i} = \begin{cases} \min \left(LAI_{max,i}, LAI_{d-1,i}^{\omega_{1,GDD,i}} \cdot GDD_{d,i} \cdot \omega_{2,GDD,i} + LAI_{d-1,i} \right), \text{leaf-on}, T_{base,GDD,i} > T_{d-1} \\ \max \left(LAI_{min,i}, LAI_{d-1,i}^{\omega_{1,SDD,i}} \cdot SDD_{d,i} \cdot \omega_{2,SDD,i} + LAI_{d-1,i} \right), \text{leaf-off}, T_{d-1} < T_{base,SDD,i}, \end{cases} \quad (D1)$$

where $LAI_{d,i}$ is the daily LAI of vegetation type i , $LAI_{max,i}$ and $LAI_{min,i}$ are the maximum and minimum LAI values, $GDD_{d,i}$ is the growing degree days calculated from days when air temperature is over $T_{Base,GDD,i}$, $SDD_{d,i}$ is the senescence degree days calculated from days when the temperature is below $T_{Base,SDD,i}$, and T_{d-1} is the mean daily temperature from previous day. $\omega_{1/2,GDD/SDD,i}$ are the growing or senescence rates.

The originally used parameters for the Swindon site in an earlier study (Ward et al., 2016) were good enough for simulating surface energy balance components but as F_{pho} is more sensitive for LAI than the latent heat flux, better LAI development is needed. In the absence of on-site LAI measurements, we obtained the observed LAI from the Visible Infrared Imaging Radiometer Suite Leaf Area Index (VIIRS LAI) Version 2 data product (Myneni, 2023) with a resolution of 500 m for 2018–2022. SUEWS was run for these years using ERA5 reanalysis data using the same surface information as in the run used to evaluate the parameters against the EC measurements. LAI parameters (Table D1) were modified to better represent the seasonal variability of LAI (Fig. D1).

Table D1. Comparison of the original and modified LAI parameters at the Swindon site.

LAI parameters	Original	Modified
GDD_{full} (°C)	300	300
SDD_{full} (°C)	-450	-200
$\omega_{1,GDD}$	0.04	0.04
$\omega_{2,GDD}$	0.001	0.002
$\omega_{1,SDD}$	-1.5	-1.5
$\omega_{2,SDD}$	0.0015	0.015

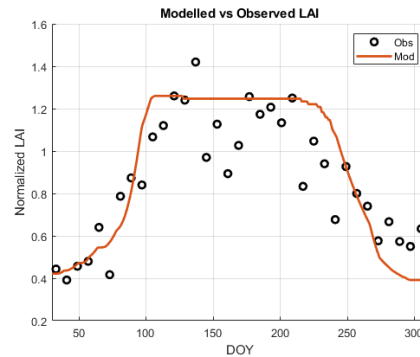


Figure D1. Normalized average leaf area index (LAI) values observed from VIIRS (Obs) and modeled by SUEWS (Mod) between 2018–22.



Appendix E: Studied surface conductance parameter selection cases and their model performance

In this study the impact of a total of 18 different parameter selection cases were tested on SUEWS model simulations in Swindon and Minneapolis. For five out of these, a more detailed examination was made. Table E1 list the different cases and the model performance of these cases are shown in Figs. E1 and E2 and Tables E1 and E2

Table E1. Different surface conductance parameter case choices used in the study. The different cases use parametrisations derived from observations made over La1 = Lawn in Helsinki, La2 = Lawn in Minneapolis, LV = low vegetation, DF = deciduous forest, EF = evergreen forest, TA = Street trees (Tilia) (see Table 2 for details).

Case	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
Conductance	La1	La1	La1	La2	La2	La2	DF	DF	DF	TA	TA	TA	AL	AL	AL	PK	PK	PK
Deciduous	DF	DF	DF	DF	DF	DF	DF	DF	DF	TA	TA	TA	AL	AL	AL	PK	PK	PK
Evergreen	EF	EF	EF	EF	EF	EF	EF	EF	EF	EF	EF	EF	EF	EF	EF	EF	EF	EF
Grass	La1	La2	LV	La1	La2	LV	La1	La2	LV	La1	La2	LV	La1	La2	LV	La1	La2	LV

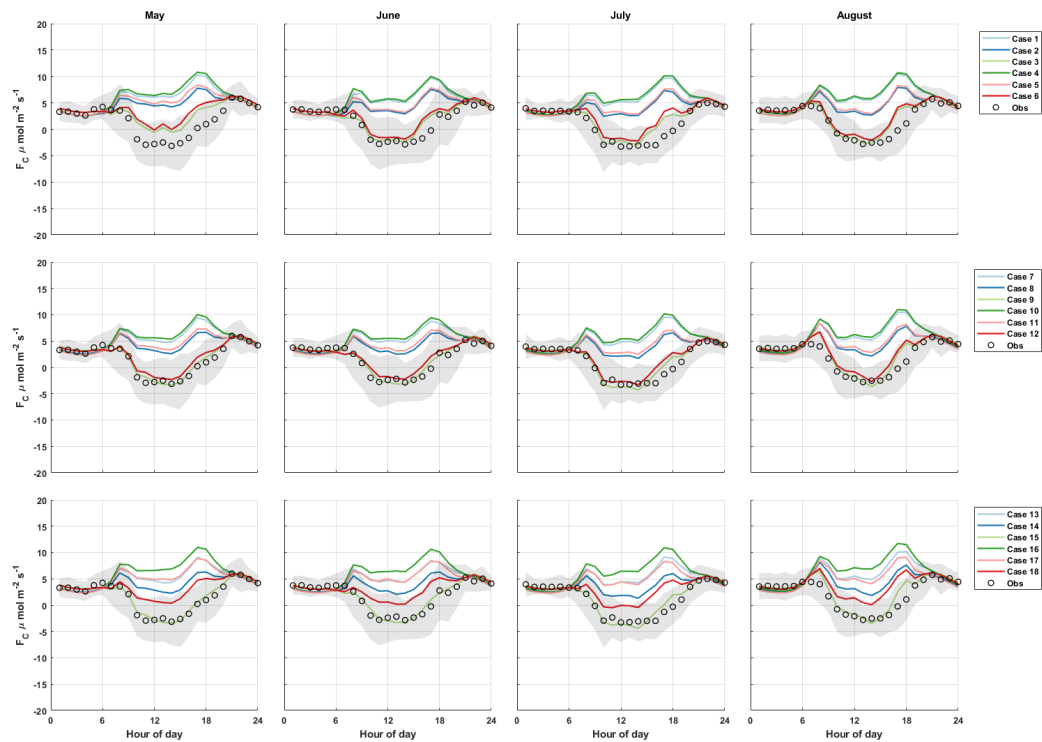


Figure E1. Average diurnal cycles of the observed and modelled hourly total CO₂ fluxes in Swindon, UK, over summer months May–August for all the 18 cases.

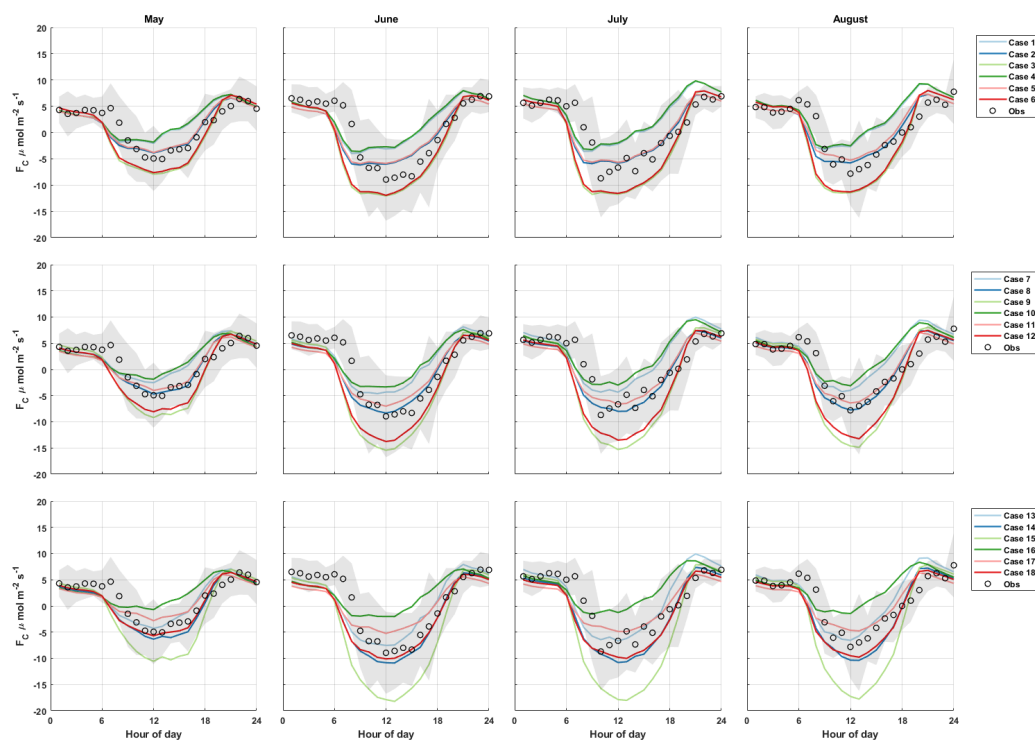


Figure E2. Average diurnal cycles of the observed and modelled hourly total CO₂ fluxes in Minneapolis, US, over summer months May–August for all the 18 cases.



Table E2. Performance metrics (R, RMSE, MAE) across Cases 1 to 18 against observations in Swindon, UK, over summer months May–August.

Case	Month	R	RMSE	MAE	Case	Month	R	RMSE	MAE
1	May	-0.06	6.52	4.86	10	May	-0.00	6.20	4.69
	June	-0.22	6.90	4.89		June	-0.03	6.05	4.54
	July	-0.26	7.93	5.67		July	-0.10	6.51	4.90
	August	-0.10	6.32	4.61		August	-0.07	6.07	4.60
2	May	0.15	5.47	4.05	11	May	0.25	5.08	3.82
	June	-0.09	5.89	4.04		June	0.21	4.82	3.58
	July	-0.12	6.71	4.66		July	0.22	5.01	3.72
	August	0.13	4.97	3.58		August	0.20	4.70	3.52
3	May	0.44	4.65	3.15	12	May	0.66	3.35	2.43
	June	0.17	5.77	3.75		June	0.62	3.36	2.40
	July	0.17	6.50	4.13		July	0.67	3.27	2.41
	August	0.48	4.11	2.75		August	0.64	3.22	2.34
4	May	-0.11	6.84	5.10	13	May	0.13	5.67	4.29
	June	-0.22	7.04	5.03		June	0.10	5.53	4.13
	July	-0.28	8.06	5.80		July	0.06	5.95	4.46
	August	-0.11	6.45	4.73		August	0.06	5.62	4.26
5	May	0.08	5.83	4.31	14	May	0.37	4.62	3.44
	June	-0.10	6.02	4.17		June	0.34	4.38	3.23
	July	-0.15	6.84	4.77		July	0.37	4.52	3.33
	August	0.10	5.10	3.70		August	0.33	4.31	3.19
6	May	0.42	4.69	3.23	15	May	0.68	3.41	2.48
	June	0.20	5.50	3.61		June	0.64	3.51	2.51
	July	0.16	6.42	4.10		July	0.69	3.36	2.49
	August	0.49	4.04	2.70		August	0.67	3.20	2.35
7	May	0.09	5.90	4.46	16	May	-0.14	6.80	5.13
	June	0.06	5.73	4.29		June	-0.17	6.67	5.01
	July	0.01	6.18	4.63		July	-0.25	7.15	5.39
	August	0.03	5.79	4.38		August	-0.21	6.62	4.99
8	May	0.35	4.79	3.58	17	May	0.06	5.74	4.34
	June	0.32	4.53	3.34		June	0.00	5.50	4.11
	July	0.34	4.69	3.45		July	-0.03	5.73	4.29
	August	0.31	4.44	3.29		August	-0.00	5.31	4.01
9	May	0.68	3.36	2.44	18	May	0.56	3.87	2.84
	June	0.64	3.47	2.49		June	0.53	3.69	2.67
	July	0.70	3.28	2.44		July	0.56	3.83	2.76
	August	0.67	3.22	2.36		August	0.53	3.70	2.66



Table E3. Performance metrics (R, RMSE, MAE) across Cases 1 to 18 against observations in Minneapolis, US, over summer months May–August.

Case	Month	R	RMSE	MAE	Case	Month	R	RMSE	MAE
1	May	0.51	4.88	3.69	10	May	0.52	4.76	3.62
	June	0.60	5.79	4.31		June	0.64	5.51	4.10
	July	0.49	6.44	5.04		July	0.54	6.14	4.77
	August	0.50	6.65	5.10		August	0.51	6.55	4.90
2	May	0.60	4.30	3.26	11	May	0.61	4.23	3.22
	June	0.70	5.20	3.79		June	0.73	4.98	3.67
	July	0.63	5.31	3.80		July	0.67	5.00	3.66
	August	0.62	5.29	3.75		August	0.63	5.19	3.67
3	May	0.64	5.04	3.79	12	May	0.65	5.01	3.77
	June	0.72	6.83	4.85		June	0.75	6.60	4.80
	July	0.66	7.04	4.96		July	0.70	6.77	4.99
	August	0.65	7.04	5.32		August	0.66	6.89	5.27
4	May	0.51	4.92	3.71	13	May	0.60	4.55	3.46
	June	0.60	5.79	4.32		June	0.71	5.23	3.79
	July	0.50	6.48	5.07		July	0.63	5.70	4.33
	August	0.50	6.73	5.16		August	0.59	6.16	4.64
5	May	0.60	4.30	3.26	14	May	0.64	4.55	3.46
	June	0.70	5.14	3.76		June	0.75	5.58	4.00
	July	0.63	5.25	3.79		July	0.70	5.67	4.14
	August	0.59	5.47	3.93		August	0.65	5.88	4.41
6	May	0.64	4.94	3.72	15	May	0.66	6.13	4.55
	June	0.73	6.60	4.67		June	0.76	8.54	6.36
	July	0.66	6.82	4.82		July	0.72	8.68	6.56
	August	0.65	6.84	5.18		August	0.66	8.85	6.79
7	May	0.56	4.73	3.56	16	May	0.48	4.91	3.77
	June	0.67	5.35	3.91		June	0.59	5.83	4.40
	July	0.58	5.99	4.62		July	0.48	6.29	4.91
	August	0.55	6.41	4.80		August	0.47	6.63	5.00
8	May	0.63	4.27	3.24	17	May	0.58	4.30	3.29
	June	0.74	5.00	3.58		June	0.71	5.10	3.89
	July	0.68	5.11	3.68		July	0.65	5.05	3.79
	August	0.64	5.29	3.81		August	0.61	5.16	3.61
9	May	0.66	5.35	4.00	18	May	0.63	4.44	3.37
	June	0.75	7.22	5.27		June	0.74	5.56	3.97
	July	0.71	7.43	5.52		July	0.68	5.78	4.12
	August	0.67	7.53	5.80		August	0.64	5.89	4.35



470 *Author contributions.* HL, MH and LJ conceptualized the study. HL and AK executed the model simulations and contributed to the software development. HL, AK, JM and HW contributed to the data curation. HL performed the formal analysis with AK, MH and LJ contributing to the visualization. HL, AK and LJ acquired funding. MH and LJ supervised the research planning. HL, AK, MH, and LJ contributed to the preparation of the original draft. All authors contributed to the writing (review and editing) process.

Competing interests. The authors declare that they have no conflict of interest.

475 *Code and data availability.* The SUEWS model code (version 2020) used in this study is openly available at <https://zenodo.org/records/5723970>. The model inputs and outputs, fitting procedures, observations used for parameters fitting, and datasets used in the analysis are openly available at <https://doi.org/10.5281/zenodo.22085968>

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