



DART-based model for three-dimensional scaling of energy balance from individual leaves to plant canopies

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Abstract. Spatial heterogeneity of vegetation canopies significantly influences the ecosystem energy exchange and gross primary production (GPP) by affecting processes, such as, the photosynthetic light absorption, energy distribution, and carbon fixation. Conventional one-dimensional (1D) models cannot account for horizontal structural diversity of complex canopies as, for instance, sparse row crops or crops in early growth stages. Therefore, the primary aim of this study was to enhance the accuracy of GPP estimations by incorporating three-dimensional (3D) plant structural complexity. To achieve this goal, a first version of the 3D energy balance DART-EB model was developed by combining the Discrete Anisotropic Radiative Transfer (DART), effectively capturing full 3D canopy structure, with modified energy balance (EB) equations originating from the 1D model SCOPE. Unlike the 1D approach, DART-EB iteratively resolves EB for individual elements of a 3D soil–vegetation scene (i.e., soil surface, plant leaves, and stems) separately. High computational efficiency of DART's LuxCorRender Monte Carlo bi-directional photon-path tracing algorithm allows to compute emitted and absorbed radiation per side of a leaf-representing triangular facet. To verify DART-EB performance, we first cross-compared its results with outputs of the widely used SCOPE model for a virtual homogeneous canopy. A strong consistency between the two models was confirmed by their high agreement in simulated net photosynthesis (d-index = 1; RRMSE = 3 %). Once verified, DART-EB was tasked to perform a comparison between geometrically-explicit vertically-homogeneous and spatially-heterogeneous vineyard canopies. Omitting the spatial heterogeneity of a vine canopy structure led to 44 % RRMSE in simulated net photosynthesis. Further comparison of DART-EB outputs against eddy-covariance measurements of an alfalfa crop in Spain revealed a significantly lower error (RRMSE = 8 %) for its genuine than for a homogeneous canopy representation (RRMSE = 20 %). The spatially-explicit digital 3D representations of alfalfa field were reconstructed from their in-situ RGB photographs. The error reduction was caused by more accurate modelling of a total absorbed photosynthetically active radiation by chlorophylls, enabled by a realistic 3D spatial distribution of the alfalfa foliage. The presented first version of DART-EB continues to be further developed, aiming to increase the computational accuracy, efficiency, and applicability to structurally highly complex canopies (e.g., forests) and large landscapes.



1 Introduction

Gross primary production (GPP) provides insights into the global carbon cycle influenced by various environmental factors (Anav et al., 2015). It is, therefore, of a significant interest to society, especially to food producers, economists, and policymakers, especially, in the context of current climate change. Recent energy balance (EB) models can simulate CO₂ assimilation and GPP in various vegetation canopies. Their use is primarily focused on modelling and retrieval of biochemical parameters, such as maximum carboxylation velocity (V_{cmax}), using predominantly a one-dimensional (1D) radiative transfer scheme (e.g., Prikaziuk et al., 2023). Since spatially heterogeneous canopy structure profoundly affects radiative transfer and energy exchange processes, neglecting its complexity can lead to significant uncertainties in model outputs. Accuracy differences between 1D and three-dimensional (3D) radiative transfer approaches that are capable of capturing canopies' spatial heterogeneity were demonstrated, for example, by Kobayashi et al. (2012). A finer geometric detail allows for more precise spatial representation of canopy heterogeneity as well as the ground topography beneath. Hence, moving from a simplified “big-leaf” canopy representation towards approaches based on 3D representations of plant structural components — e.g., triangulated geometric primitives of leaves, branches, and stems — can improve modelling of leaf temperature and, subsequently, evapotranspiration and CO₂ fluxes in structurally complex vegetated ecosystems. By discretizing a simulated scene into spatially explicit triangular facets and/or distribution of volumes filled with turbid representation of vegetation (Knyazikhin and Marshak, 1991), a 3D model can also reproduce directly spatial variations in soil temperature and evaporation of sunlit and shaded surfaces. Moreover, incorporating the elevation of the soil facets allows for representing real topography of a complex and ragged terrain and, consequently, elevation-driven microclimatic differences. When used in a 3D radiative transfer model, such a detailed plant and soil representation facilitates better their interactions with light, resulting in more accurate radiative budget of scattered, absorbed, and emitted fluxes per facet and/or turbid volume of the simulated geometrical objects. This provides a solid cornerstone for developing an advanced energy balance (EB) model for structurally complex vegetation canopies, incorporating biochemical photosynthetic and aerodynamic resistance models with all relevant heat fluxes and heat storage components.

At the canopy scale, the SCOPE model (Van Der Tol et al., 2009; Yang et al., 2020) was designed and tested to resolve a complete energy balance of 1D canopy representations. More recently, the 3D HELIOS (Bailey, 2019; Wang et al., 2026), FLiES-SIF (Sakai et al., 2020), CanVeg2 (Béland et al., 2026), WPS (Zhao et al., 2022), and DART (Regaieg et al., 2023) models were developed to account for plant structural heterogeneity and variability in leaf biochemical properties. To reduce input requirements and computational load, FLiES-SIF assumes a fixed leaf temperature instead of simulating the full energy balance, including stomatal conductance, and photosynthetic processes. Similarly, CanVeg2 adopted a look-up table approach to manage the high computational load of the 3D FLiESvox model (Kobayashi and Iwabuchi, 2008). Contrary, HELIOS and WPS do model photosynthetic light-use efficiency through a dedicated module resolving energy balance, including net radiation, heat fluxes, and photosynthesis in 3D canopies.



Despite its modelling complexity and a high computational demand, a full integration of incoming-outcoming energy balance including soil–plant heat fluxes, photosynthesis-related processes, and plant canopy aerodynamic resistance is considered to be essential for assessing functionality of photosynthesis, evapotranspiration, and soil–plant–atmosphere thermal energy exchange at the scale of individual leaves. Modelling of these processes at such detailed spatial scale can enhance our understanding of vegetation functioning across diverse canopy structures and environmental conditions. In this study, we leveraged for this purpose 3D functional capabilities of the Discrete Anisotropic Radiative Transfer (DART) model (Gastellu-Etchegorry et al., 2015; Wang et al., 2022) linked to its new extension for energy balance modelling called DART-EB. The primary objective of this paper is to introduce a design of the process-based DART-EB model. The second objective is to demonstrate its functionality and performance by answering the following three research questions: (1) does DART-EB reproduce the energy balance of a 1D canopy in a consistent manner as the reference model SCOPE, (2) what is the simulated impact of a row-crop 3D canopy structure (e.g., vineyard) on key energy balance outputs as CO₂ assimilation rates or leaf and soil temperatures, and (3) how accurately can DART-EB estimate the net photosynthesis of a spatially heterogeneous alfalfa crop in its early growth stage?

2 Material and methods

2.1 Generic design of DART-EB

The methodological flowchart of the DART-EB algorithm is illustrated in Figure 1. Once the initial values for temperature and atmospheric conditions are assigned, DART computes three key radiation budget components: (1) the absorbed photosynthetically active radiation (APAR) by chlorophyll (P_n), serving as an input for the photosynthesis model to calculate CO₂ assimilation, (2) the net bottom-of-atmosphere radiation (R_n), accounting for direct and diffuse irradiance from the sun and atmosphere, and (3) the net thermal radiation (R_t) of triangular scene elements' surfaces, such as soil and leaf facets. R_t is recalculated iteratively, using the temperatures of individual facets as input. The energy balance equation computes equilibrium between an incoming net radiation energy and energy of heat storage and outgoing heat fluxes. The difference between them represents the energy balance error and is computed per every element (i.e., soil and leaf) facet. The temperatures of the scene elements' surfaces are iteratively adjusted according to the actual energy balance error. The model iterates until all energy balance errors fall below a defined threshold (e.g., 1 W m⁻²). To ensure a reasonable efficiency and prevent excessive computational time for a negligible increase in accuracy, a maximum iteration limit (typically 7 to 10 iterations) can be enforced. After reaching the energy convergence, DART-EB outputs the surface temperature, assimilation of CO₂, and key energy flux components of each element facet.

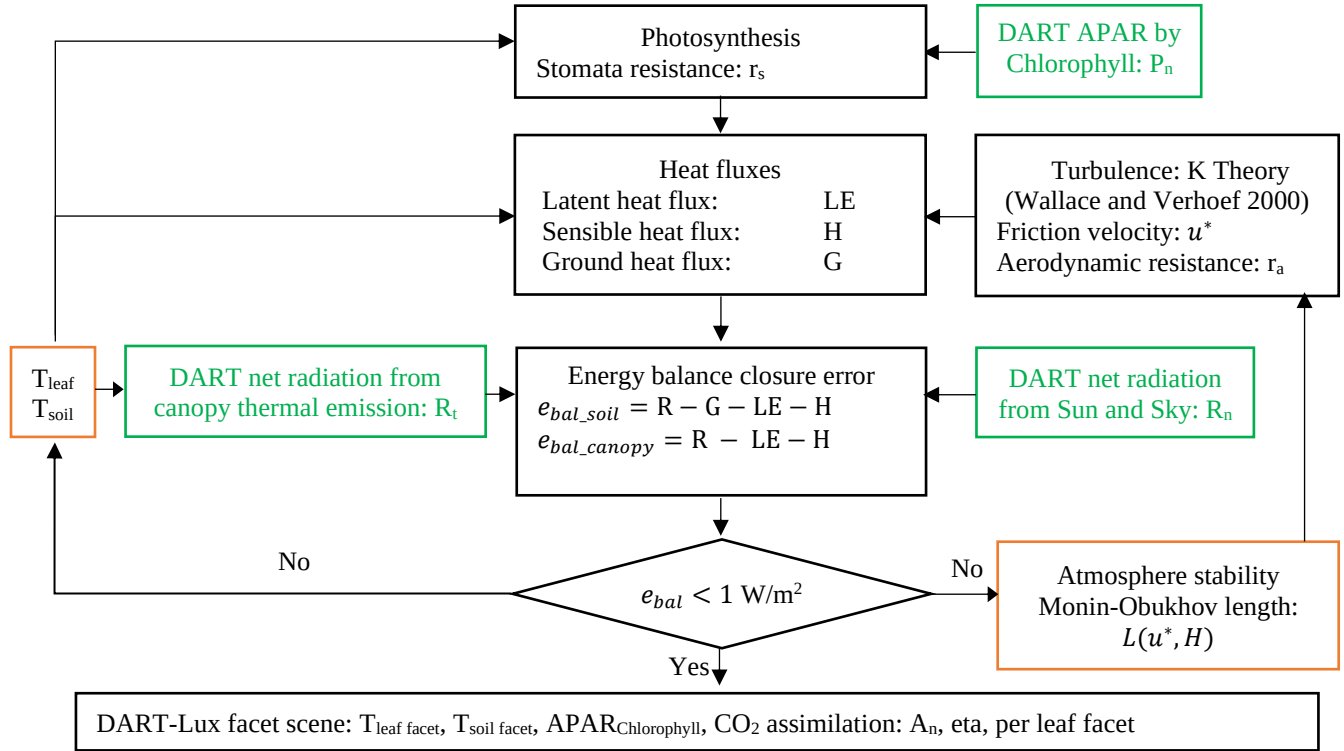


Figure 1: Flowchart depicting schematically all components of the DART-EB algorithm and their functional linkages.

2.1.1 DART 3D radiative budget modelling

DART, developed since 1992 by the CESBIO laboratory in Toulouse, France (<https://dart.omp.eu>), is a comprehensive, physically-based, model of 3D radiative transfer (Gastellu-Etchegorry et al., 1996), in natural and urban landscapes, and also in the atmosphere. Its spectral domain includes the short waves and long waves over $[0.3\mu\text{m}, 50\mu\text{m}]$. Land surface elements such as trees can be simulated as a combination of facets, and also turbid and fluid volumes. The two radiative transfer modes of DART version 5, i.e., the photon-flux tracking DART-FT (Yin et al., 2013, 2015) and the Monte Carlo bi-directional photon-path tracing DART-Lux (Wang et al., 2022), can be used to compute vegetation and soil radiative budgets within the DART-EB framework. In this study, we employed the DART-Lux mode through 3D plant representations built out of geometrically-explicit triangular facets.

DART calculates three key radiation components. (1) The first key component is APAR by chlorophyll (P_n ; radiation absorbed within the 400–780 nm spectral range) for every plant leaf facet. The simulated P_n is converted from W m^{-2} to $\mu\text{mol m}^{-2} \text{s}^{-1}$ as detailed in Appendix A. (2) The second key component is the total absorption R_n of solar and sky radiation from 0.4 to 50 μm by soil and vegetation cover. Since P_n and R_n are independent of vegetation and soil temperature, they are computed only once and remain constant through the energy balance iterations. (3) The third key component is the net thermal radiation



emitted by vegetation and soil without accounting for atmosphere, R_t . It is calculated as the difference between the absorbed and emitted thermal radiation of each surface's facet using either the Planck or the Stefan-Boltzmann equation for each new up-date of the scene 3D temperature, at every energy balance iteration.

2.1.2 Energy balance modelling

In the 3D energy balance model framework, a net radiation is distributed over turbulent heat fluxes and heat storage of triangular facets in the simulated scene that represent stems, leaves, and soil surfaces as distinct elements. The energy balance equation for each facet is then given by:

$$R - H - L.E - G = 0, \quad (1)$$

where R is the net radiation, defined as $R = R_n + R_t$, H is the sensible heat flux, $L.E$ is the latent heat flux, and G is the heat storage term (all in W m^{-2} , as detailed in Appendix B). Heat storage G is considered only for soil facets, as the heat capacity of leaves and thin stems (e.g., alfalfa stems' diameter is ranging from 2 to 4 mm) are too small and considered as negligible (Galedar et al., 2008; Meyers, 2004). For stems, sensible heat flux is considered but, assuming no transpiration, their latent heat flux is neglected. Following Eq. (1), the energy balance closure error per facet of a modelled element (i.e., stem, leaf, and soil) is computed as:

$$\text{error}_{\text{ballance}}^{\text{stem}} = R^{\text{stem}} - H^{\text{stem}}, \quad (2)$$

$$\text{error}_{\text{ballance}}^{\text{leaf}} = R^{\text{leaf}} - L.E^{\text{leaf}} - H^{\text{leaf}}, \quad (3)$$

$$\text{error}_{\text{ballance}}^{\text{soil}} = R^{\text{soil}} - L.E^{\text{soil}} - H^{\text{soil}} - G. \quad (4)$$

2.1.3 Photosynthesis modelling

The Farquhar biochemical model (Farquhar et al., 1980; Von Caemmerer and Farquhar, 1981), originally based on gas exchange principles incorporating the properties of the ribulose-1,5-bisphosphate (RuBP), the carboxylase/oxygenase (Rubisco), and an electron transport capacity in response to variations in APAR, leaf temperature, and the partial pressures of O_2 and CO_2 , was implemented to simulate the photosynthesis. Building upon this framework, a semiempirical model of leaf stomatal conductance was subsequently introduced (Farquhar and Wong, 1984; Ball et al., 1987), differentiating between C_3 and C_4 plants via two parameters (Collatz et al., 1991): i) Ball Berry slope and ii) intercept (Sellers et al., 1996). To simulate C_4 plant photosynthetic pathways, we have incorporated the empirical model of photosynthesis developed by Von Caemmerer (2000 and 2013). In addition, an empirical photosynthetic model including a solar-induced chlorophyll fluorescence (SIF) (Christiaan van der Tol et al., 2014) was incorporated in DART-EB. This allows for computing the SIF microclimatic correction factor (η) for the fluorescence quantum efficiency (FQE) of Photosystem II (PSII) in leaves exposed to varying light intensities. The factor η ensures correct initiation of the leaf fluorescence emissions in the leaf radiative transfer model



Fluspect-Cx (Vilfan et al., 2016, 2018), when scaling SIF through DART to the top of the canopy (Malenovsky et al., 2021). The third implemented photosynthetic algorithm is an advanced Johnson-Berry modification of the Farquhar model (Johnson and Berry, 2021; Johnson et al., 2021). The Johnson-Berry model incorporates mechanistically the functioning of the Cytochrome b6f complex in regulating the steady-state electron transport flowing through PSII to photosystem I (PSI) and allows user to decompose the chlorophyll fluorescence signals into the separate contributions from PSII and PSI. This mechanistic model extends its applicability beyond the traditional to C3 and C4 plants, by accommodating also the C3-C4 intermediate species. Figure 2 illustrates the workflow of the implemented Johnson-Berry model, retaining the stomatal conductance model (Brent, 1971; Collatz et al., 1991) to calculate CO₂ concentrations inside and outside the leaves.

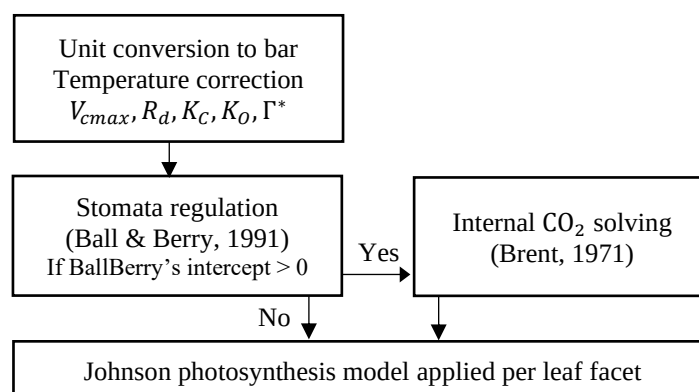


Figure 2. The flowchart of the Johnson-Berry biochemical photosynthesis model as integrated in DART-EB.

2.1.4 Aerodynamic resistance modelling

To account for the influence of wind cooling on heat transfer and air (gas) exchange between the canopy and atmosphere, aerodynamic resistance is computed using the momentum roughness length (z_{om}) and displacement height (d), as described in *Modelling Interactions in Mixed-Plant Communities* (Verhoef et al., 1997; Wallace et al., 2000). For calculating stem heat fluxes, the aerodynamic resistance of plant stems is assumed to be equal to that of leaves. The total surface area of the vegetation used to compute aerodynamic resistance is the sum of the one-side leaf area and half of the stem area, as only half of the stem surface is expected to obstruct a wind flow. To prevent evapotranspiration from stems, the stems' resistance is set, by default, to zero.

2.1.5 Modelling of leaf and soil optical properties

Leaf optical properties (i.e., leaf reflectance and transmittance) are required to compute the radiative budget in DART. Leaf reflectance and transmittance within the spectral range of 0.4 μm to 2.4 μm can be reproduced using the essential leaf biochemical traits as inputs in the PROSPECT (Jacquemoud and Baret, 1990; Féret et al., 2021) or Fluspect-Cx (Vilfan et al., 2016, 2018) models. Leaf optical properties for the thermal spectral domain (i.e., from 2.4 μm to 50 μm) must be specified from external field or laboratory measurements. In-situ measurements can also be used to parametrize soil reflectance.



Optionally, the bare soil optical properties can be simulated and imported from the soil radiative transfer model MARMIT (Babliet et al., 2018).

2.2 DART-EB functionality – Intercomparison of simulations for simplified and close-to-reality canopy representations

2.2.1 Homogeneous quasi-turbid representation comparable to a SCOPE canopy

To verify the consistency and access the functionality of DART-EB version 1.0, we compared its output quantities with the corresponding products simulated by the 1D SCOPE model (version 2.1, 2026) for a simple homogeneous plant-canopy. SCOPE is considered as a well-established energy balance model (Van Der Tol et al., 2009; Yang et al., 2020) that was validated against flux tower observations (Prikaziuk et al., 2023). As in the SAIL radiative transfer model (Verhoef, 1984), a vegetation canopy is represented by homogeneous layers filled with a turbid medium (i.e., infinite number of infinitely small leaves with a given leaf volume area density ($\text{m}^2 \text{m}^{-3}$) and leaf angular distribution (LAD)). To ensure fully-comparable canopies in both models, the turbid medium of SCOPE was mimicked in DART by a juxtaposed 3D box (Fig. 3a) filled with small triangular facets (area of 0.3 cm^2). This quasi-turbid canopy represented the total one-sided leaf area of 2 m^2 (c. 66,666 triangles) within a ground projection area of 1 m^2 and a canopy height of 1 m (i.e., $\text{LAI} = 2$), distributed according to the spherical LAD. The thermal infrared properties (i.e., wavelengths of $8\text{--}14 \mu\text{m}$) can be simulated through mechanistic modelling considering leaf water content (Xu et al., 2023). Nonetheless, to represent a generalized leaf-type across various vegetation conditions, the leaf reflectance and transmittance in the thermal infrared domain were set based on the average values of all leaf optical properties available in the DART database to 0.027 and 0.01, respectively. The equally-set values of both models' inputs, including leaf biochemical and biophysical parameters, are detailed in the Supplementary information document.

2.2.2 Spatially-heterogeneous quasi-turbid canopy

To investigate the impact of foliage spatial heterogeneity in a quasi-turbid vegetation canopy representation, the previous DART scene was modified by repositioning the triangular leaf elements toward the centre of the scene, forming denser vegetation columns. This arrangement represents a row-crop in a quasi-turbid setup (Fig. 3b). Although the total canopy LAI and LAD stayed unchanged, the LAI per row (i.e., foliage column) increased to 10 due to a denser foliage clumping in each column that occupies a ground area of 0.1 m^2 and contains 1 m^2 of leaf area.

2.2.3 Spatially homogeneous and heterogenous vineyard canopies

To explore differences between the quasi-turbid vegetation canopy and close-to-reality geometrically explicit canopy representations, we conducted simulations using 3D vineyard scene built with realistic 3D virtual vine (*Vitis vinifera*) plants. First, we carried out a simulation for a 1D horizontally-homogeneous vineyard (Fig. 3c), where realistic vine leaves were randomly positioned horizontally while maintaining their genuine canopy height and leaf angularity, preserving a total LAI of 8.8 and a realistic LAD. The complementary reference simulation was conducted for a close-to-reality, 3D spatially-

heterogeneous vineyard (Fig. 3d) with the scene width of 54.8 m, consisting of 2 m-tall vine shrubs arranged in 20 rows with a row spacing of 2.74 m. The planting interval of 1.83 m and 20 plants per row resulted in a row length of 36.6 m. To ensure the full comparability between the two scenarios, the LAI and LAD were kept identical and wooden stems were removed from both simulations. The solar zenith angle was set to 30°, the solar azimuth angle was aligned parallel to the row direction, and all other input parameters were kept identical to those used in the previous quasi-turbid canopy simulations.

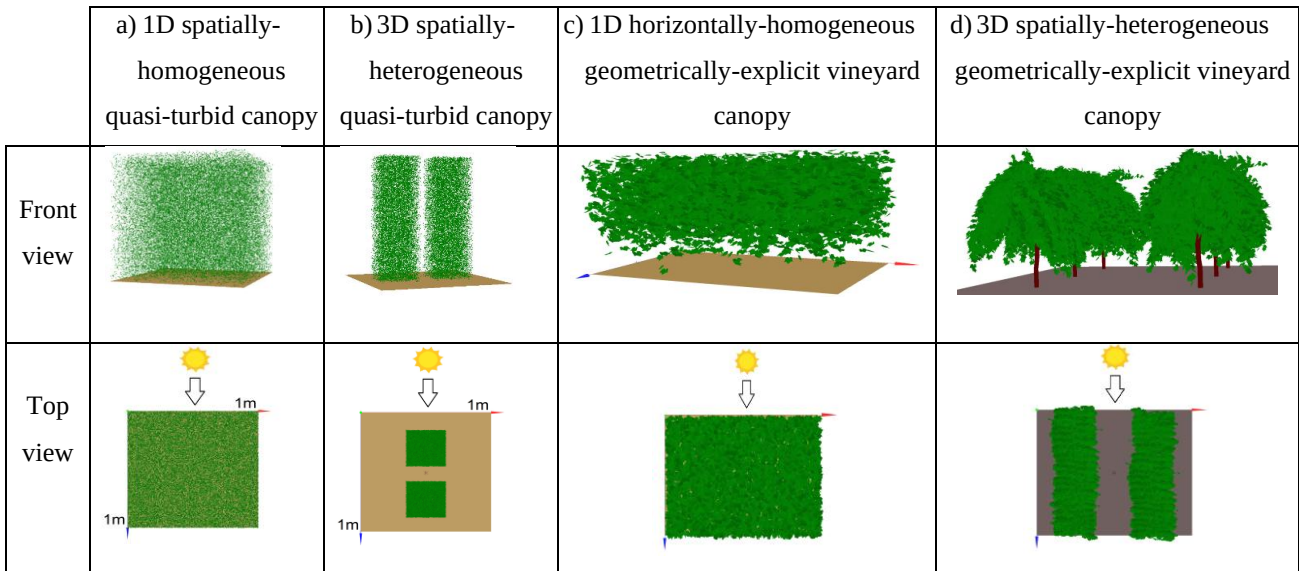


Figure 3: The four canopy architectures used in the DART-EB simulations: (a) 1D spatially-homogeneous quasi-turbid canopy – leaves approximated by small triangular facets (area of 0.3 cm²) are replicating a virtual SCOPE’s 1D canopy, (b) 3D spatially-heterogeneous quasi-turbid canopy – leaves approximated by 0.3 cm²-small triangular facets are clumped in columns representing plots of a virtual row-crop, (c) 1D horizontally-homogeneous geometrically-explicit vineyard canopy – a virtual field of horizontally randomised realistic vine leaves, and (d) 3D spatially-heterogeneous geometrically-explicit vineyard canopy – a field of realistic vine leaves and plants arranged in parallel rows.

2.3 Comparison of DART-EB simulations and field measurements of an alfalfa canopy

To assess the accuracy performance of DART-EB, we compared its simulated net photosynthesis for a realistic alfalfa (*Medicago sativa*) agricultural crop with corresponding field measurements acquired during the LIAISE experimental campaign. The measurements were collected at an agricultural field located near Lleida in Spain (altitude of 240 m. a. s. l.) in summer 2021. Detailed 3D representations of the alfalfa plants were created with the open-source graphical software Blender (<https://www.blender.org>) based on multiple RGB photographs of representative plants taken in the field. A 1 m² 3D scene was subsequently constructed (see the top view in Fig. 4a and the side view in Fig. 4c), ensuring the spectral fit between TOC reflectance measured in field and its complementary DART simulation. Figure 4b shows the leaf area index in a 10 x 10 cm grid, representing the vegetation clumping pattern, as used to parametrise the 3D scene. To ensure the architectural



representativeness of the simulated alfalfa crop, the scene LAI was assessed against in situ measurements acquired across 132 field locations, which yielded a mean value of 1.33 and a standard deviation of 0.58 (González-Armas et al., 2024). The mean LAI derived from the reconstructed geometrically-explicit 3D scene (Fig. 4b) was 1.56 with the standard deviation of 0.96 (Regaieg et al., 2025), which embraces the observed range of natural variability and aligns closely with the measured values, confirming the structural realism of the simulated canopy. To investigate the influence of the foliage spatial homogeneity, the realistic alfalfa canopy scene was modified by randomly placing the leaves in both horizontal directions according to their normal distribution. This rearrangement effectively removed the natural foliage clumping of the original scene and created a spatially-homogeneous geometrically-explicit canopy representation, maintaining the same LAI and leaf angle distribution (LAD) (Fig. 4d, e).

Both leaf optical properties (i.e., reflectance and transmittance) were simulated from the biochemical traits (i.e., contents of chlorophyll a+b, carotenoids, water, and dry matter) retrieved from in-situ leaf reflectance measurements through an inversion of the leaf radiative transfer model PROSPECT (Regaieg et al., 2025). The soil reflectance for the electromagnetic spectrum between 0.4 and 2.4 μm was measured in-situ with an optical soil probe attached to an ASD FieldSpec-4 spectrometer. Leaf optical properties from 2.4 μm to 50 μm were set equal to 0.01. The diurnal DART-EB simulation was conducted for the measurement day of July 17, 2021. The virtual alfalfa canopy was illuminated every 30 min by a bottom-of-atmosphere direct and diffuse solar irradiance, simulated for the corresponding date by Regaieg et al. (2025).

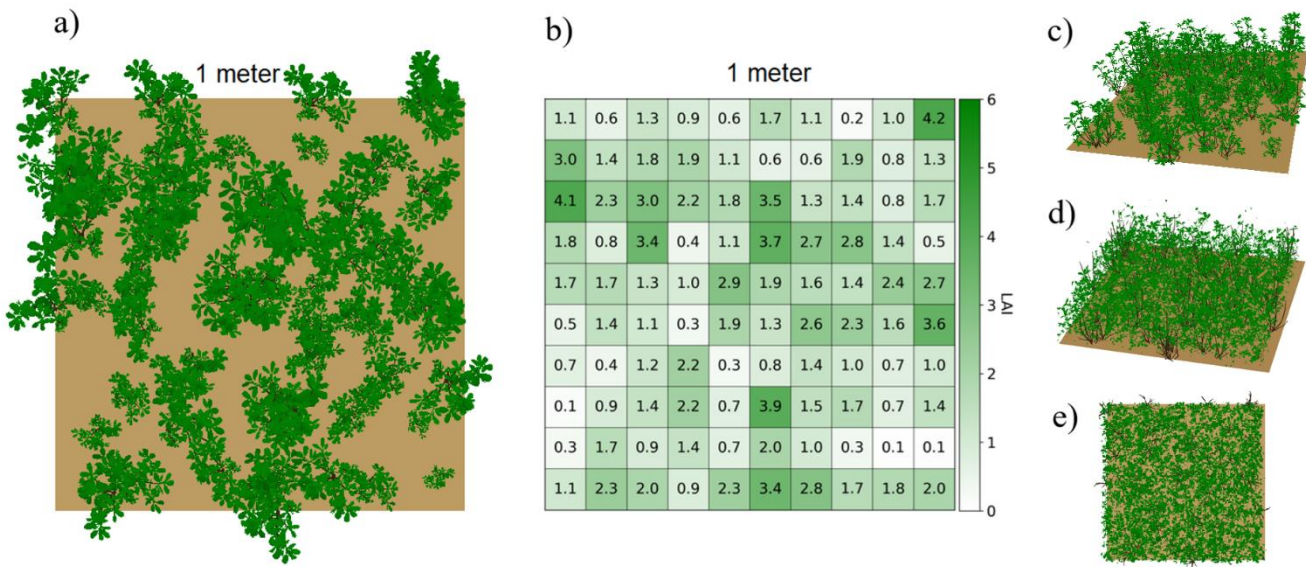


Figure 4: 3D canopy representations and structural parameterisation of the alfalfa crop. (a) Top view of the geometrically-explicit 3D alfalfa scene reconstructed from field photographs. (b) The corresponding Leaf Area Index (LAI) grid at 10 cm resolution, revealing the horizontal clumping pattern. (c) Side view of the reconstructed scene. (d) a side view, and (e) Top view of the horizontally-randomised (homogeneous) alfalfa scene, created by removing the canopy gaps while preserving the scene's total LAI, vertical structure, and leaf angularity.



The maximum rate of RuBisCO carboxylase activity (V_{cmax}) was obtained from Wynaendts, 2022, which reported a mean value of $215 \mu\text{mol m}^{-2} \text{s}^{-1}$ for several leaves measured on July 17, 2021. To accurately simulate heat fluxes in DART-EB, leaf gas-exchange measurements (González-Armas et al., 2024) were used to fit the Ball-Berry equation (Eq. 5), allowing for the derivation of the Ball-Berry slope (m) and the minimum conductance (b) (Ball et al., 1987; Collatz et al., 1991). The optimal fitted slope (m) in the linear equation:

$$g_s = m \frac{A \times rh}{C_s} + b, \quad (5)$$

where g_s is stomatal conductance, A is net assimilation, rh is leaf surface relative humidity, and C_s is leaf surface CO_2 concentration, was found to be 6.7 and the intercept (b) was equal to 0.5 (see Fig. 5).

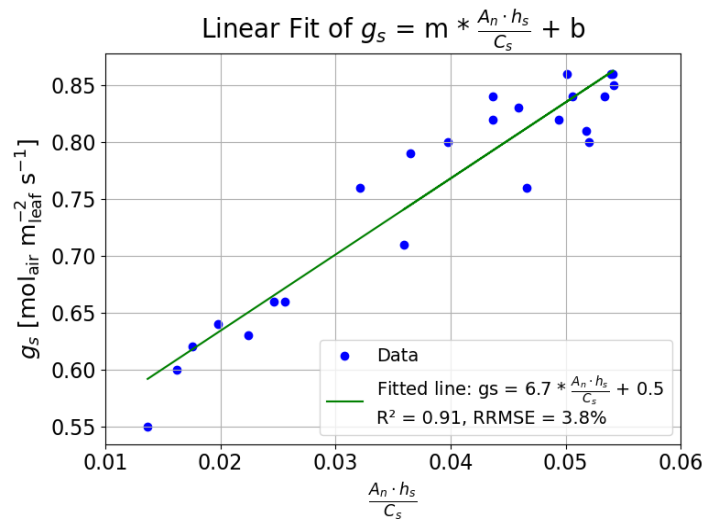


Figure 5: Parameterization of the Ball-Berry stomatal conductance model for alfalfa leaves using field measurements. The linear regression yielded an optimal slope $m = 6.7$ and a minimum conductance $b = 0.5$.

Finally, Eddy covariance measurements, published in Branch et al. (2022), and soil respiration measurements by González-Armas et al. (2024) were combined to calculate the diurnal course of net photosynthesis CO_2 assimilation of the alfalfa canopy.

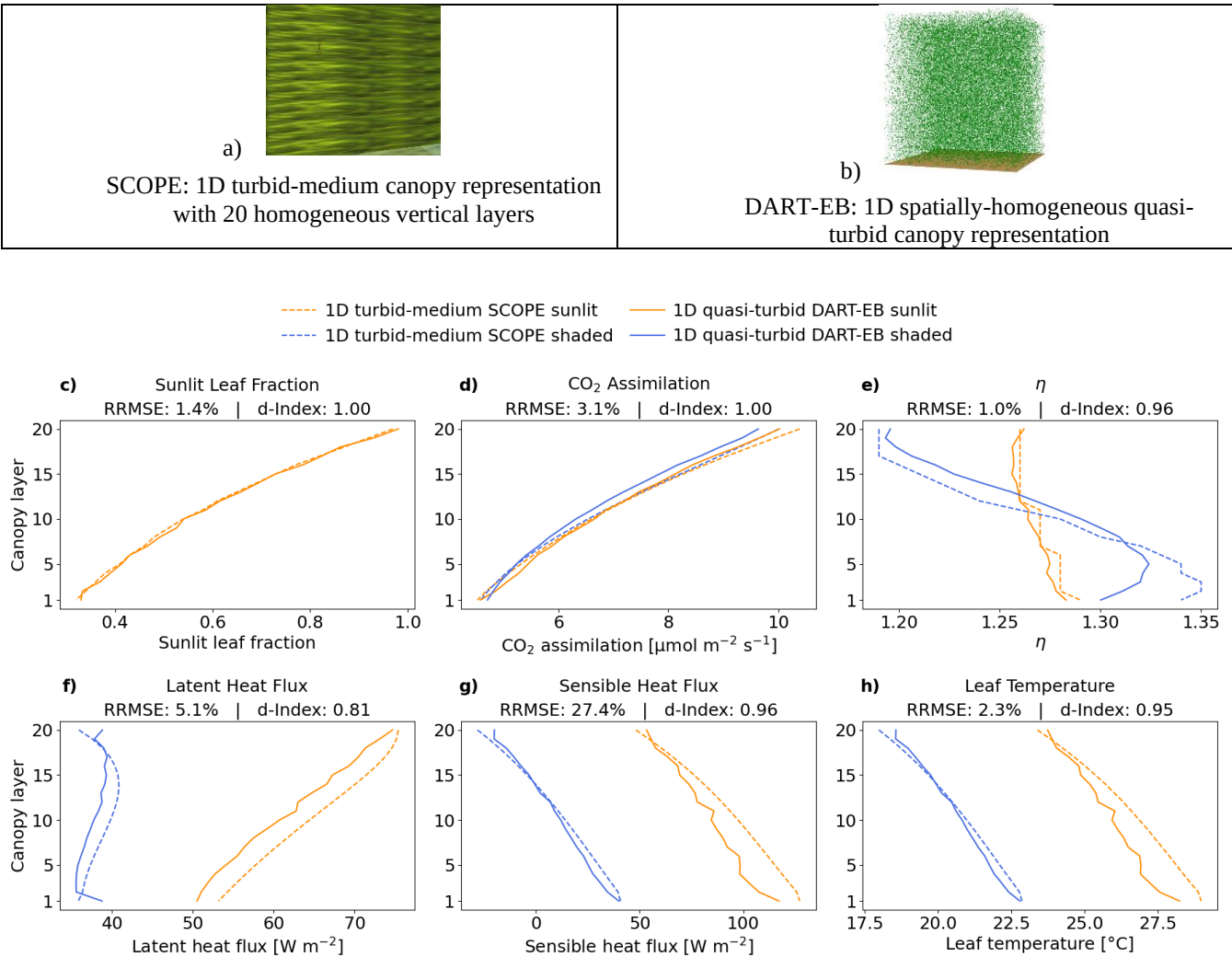
3 Results

3.1 DART-EB and SCOPE comparison for spatially homogeneous canopy representation

To assess modelling consistency between the DART-EB and SCOPE models, the vertical profiles of key physiological and energy balance variables simulated by both models for a comparable, homogeneous canopy were cross compared. Figure 6c-



h shows the canopy vertical profiles of simulated physiological and energy balance variables for sunlit and shaded leaves as computed by both models. In DART-EB, the determination of these sunlit and shaded facets is achieved through a facet-level geometric classification implemented in DART, which segments the 3D canopy elements based on their centroid positioning and local exposure to direct solar irradiance (see Appendix C). Overall, the SCOPE and DART-EB outputs produced for the turbid-medium and quasi-turbid canopies, respectively, are in a high agreement across the vertical profile of both sunlit and shaded leaf cohorts. On the one hand, fractions of sunlit leaves, and values of net photosynthesis simulated by DART-EB track closely the SCOPE outcomes, indicating a high modelling consistency. On the other hand, the η factor values, latent and sensible heat fluxes, and leaf temperature shows some differences, particularly in the middle and lower canopy layers. Yet, d-index values ranging from 0.81 to 0.96 indicate that they maintain a high agreement.



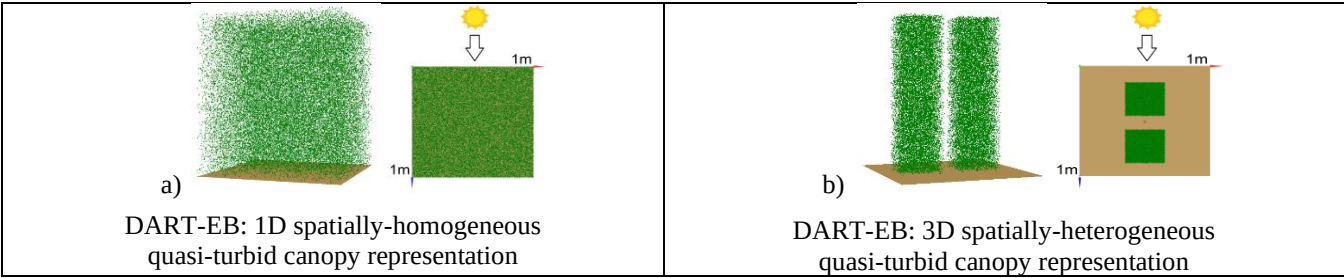
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Figure 6: Consistency between (a) SCOPE and (b) DART-EB spatially homogeneous virtual canopies (LAI = 2). (c) Canopy vertical profiles of sunlit leaf fraction. (d) Net photosynthetic CO₂ assimilation. (e) η solar-induced fluorescence scaling factor. (f) Scene latent heat flux. (g) Sensible heat flux. (h) Leaf surface temperature (dashed lines for SCOPE, and solid lines for DART-EB). Sunlit leaves are in orange, and shaded leaves are in blue. The model similarity d-index (1 ~ full agreement and 0 ~ total disagreement; see Appendix D. Index of agreement between two datasets) and the Relative Root Mean Square Error (RRMSE) were computed for both sunlit and shaded leaves together.

3.2 DART-EB simulations of spatially heterogeneous quasi-turbid canopy

While maintaining the identical total leaf area index (LAI = 2), DART-EB simulations for the spatially-heterogeneous scene revealed substantial deviations from the homogeneous reference case in both energy balance and physiological outputs (Fig. 7), as the spatially-heterogeneous scene significantly altered internal light environment. Specifically, the sunlit foliage cohort was markedly lower across all canopy layers while the shaded fraction was consistently higher (RRMSE = 134.6 %; $d = 0.58$; Fig. 7c). Consequently, while a general consistency in vertical distribution of net photosynthesis between the two cases was maintained ($d = 0.97$), the heterogeneous configuration yielded a lower magnitude in CO₂ assimilation (Fig. 7d). In contrast, the η factor demonstrated a strong difference ($d = 0.49$; Fig. 7e). The larger divergences were observed in the energy balance variables, i.e., the latent and sensible heat fluxes, as well leaf temperature (d ranging from 0.19 to 0.55; Fig. 7f, g, h).



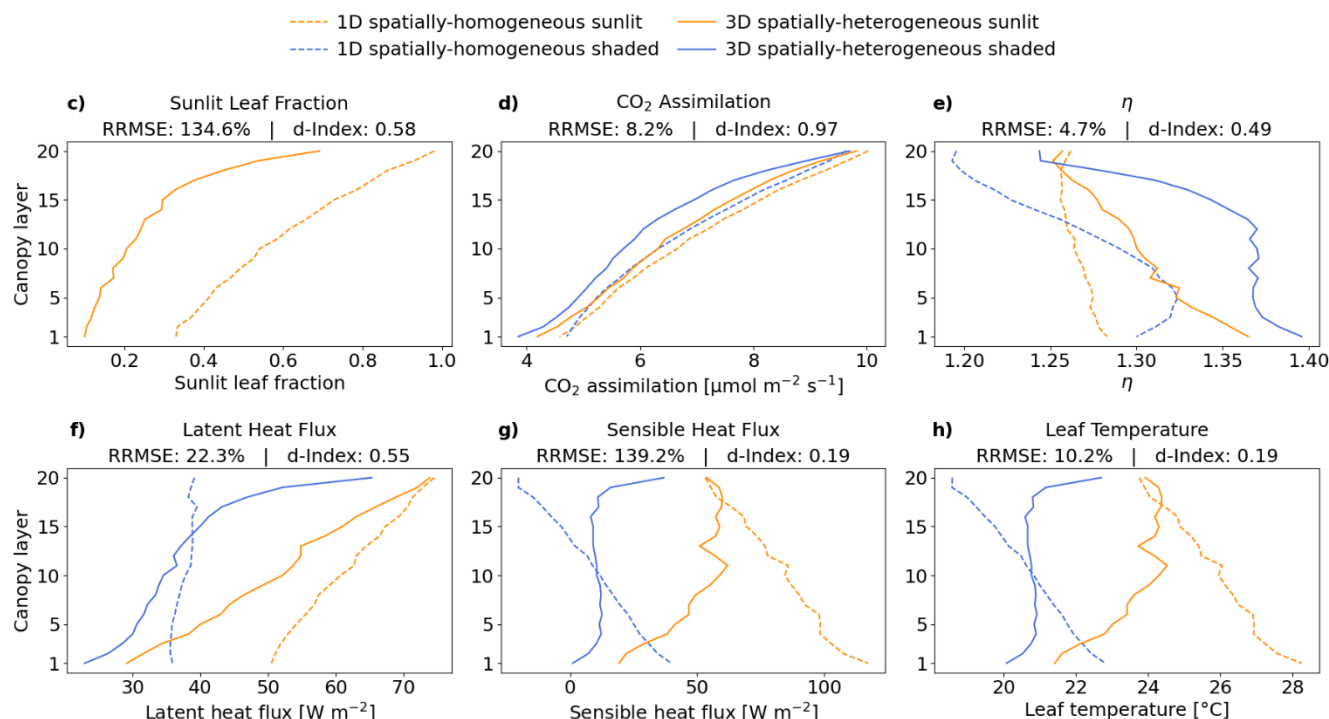


Figure 7: Vertical profiles for the (a) spatially-homogeneous reference canopy and (b) clumped row-crop architecture simulated in DART-EB. (c) Sunlit leaf fraction. (d) Net photosynthesis CO_2 assimilation. (e) η solar-induced fluorescence scaling. (f) Latent heat flux. (g) Sensible heat flux. (h) Leaf temperature. For explanation of RRMSE and the similarity d-index see caption of Figure 6.

3.3 Spatially homogeneous and heterogenous vineyard canopies

The previous experiment quantified the impacts of an artificially created foliage clumping. In this section, we investigate the differences between a spatially-homogeneous and a close-to-reality, geometrically-explicit representation of a vineyard canopy. The soil, foliage, and scene-integrated net radiative budgets, APAR by chlorophylls (APAR_{Chl}), and the net photosynthesis of both vineyard configurations are summarised in Table 1. Due to the penetration of solar radiation in the spaces between vine rows, the soil in the geometrically-explicit simulation received a higher net radiation by 11 W m^{-2} . Conversely, the homogeneous vineyard exhibited 11 W m^{-2} higher leaf-level radiation interception, which resulted in $502 \mu\text{mol photon ground m}^{-2} \text{ s}^{-1}$ higher APAR_{Chl} . This led to a reduction in net photosynthesis (A_n) by $8.6 \mu\text{mol CO}_2 \text{ m}^{-2} \text{ s}^{-1}$ for of geometrically-explicit vineyard, demonstrating a strong influence of 3D canopy architecture on photosynthetic productivity even when total biomass (i.e., LAI) is constant.



Table 1: Net radiation (R_n) of soil and foliage, chlorophyll absorbed photosynthetically active radiation ($APAR_{chl}$), and net photosynthesis (A_n) for 1D horizontally-homogeneous and 3D spatially-heterogeneous vineyard representations.

	$R_{n, \text{soil}}$ ($W\ m^{-2}$)	$R_{n, \text{foliage}}$ ($W\ m^{-2}$)	$R_{n, \text{scene}}$ ($W\ m^{-2}$)	$APAR_{chl}$ ($\mu\text{mol photons ground } m^{-2}\ s^{-1}$)	A_n ($\mu\text{mol } CO_2\ m^{-2}\ s^{-1}$)
Horizontally-homogeneous vineyard	3	298	301	1548	28.0
Spatially-heterogeneous vineyard canopy	14	287	302	1046	19.4
Absolute difference (Δ)	11	11	1	502	8.6
Relative difference (%)	79 %	4 %	0.3 %	48 %	44 %

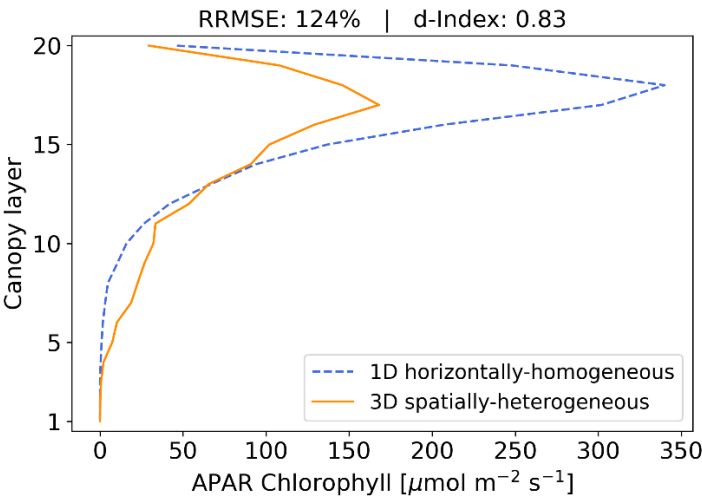


Figure 8: Vertical profiles of photosynthetically active radiation absorbed by leaf chlorophyll ($APAR_{chl}$) across the canopy height layers for 1D horizontally-homogeneous and 3D spatially-heterogeneous vineyard canopy representations.

The vertical distribution of $APAR_{chl}$ in Figure 8 illustrates how much the horizontally-homogeneous (1D) representation overestimates $APAR_{chl}$, particularly within the upper canopy layers. This divergence resulted in RRMSE of 124 %, indicating that 1D abstractions do not accurately replicate the internal light-harvesting of a clumped vineyard architecture.

Figure 9 shows canopy vertical profiles of other key physiological and energy exchange variables. In the geometrically-explicit configuration, the sunlit fraction of foliage was markedly lower in the upper part of the canopy compared to the horizontally-homogenised abstraction (Fig. 9c). Consequently, the fraction of shaded leaves followed the opposite symmetric trend, showing a deviation in the sun-light distribution between the two modelling approaches. This resulted in an overestimation of simulated net photosynthesis (A_n ; Fig. 9d) as well as the η factor (Fig. 9e) for the shaded cohort of leaves in the homogeneous architecture above the 12th canopy layer (i.e., 1.2 m height). A_n opposite pattern occurred below layer 12, where the geometrically-explicit modelling yielded higher physiological activity for both sunlit and shaded leaves. The energy balance



variables (Fig. 9f–h) demonstrate further the structural impact, as the leaf temperature, latent heat flux, and sensible heat flux for sunlit as well as shaded foliage from the middle canopy to the soil surface were found to be systematically higher in the geometrically-explicit simulation.

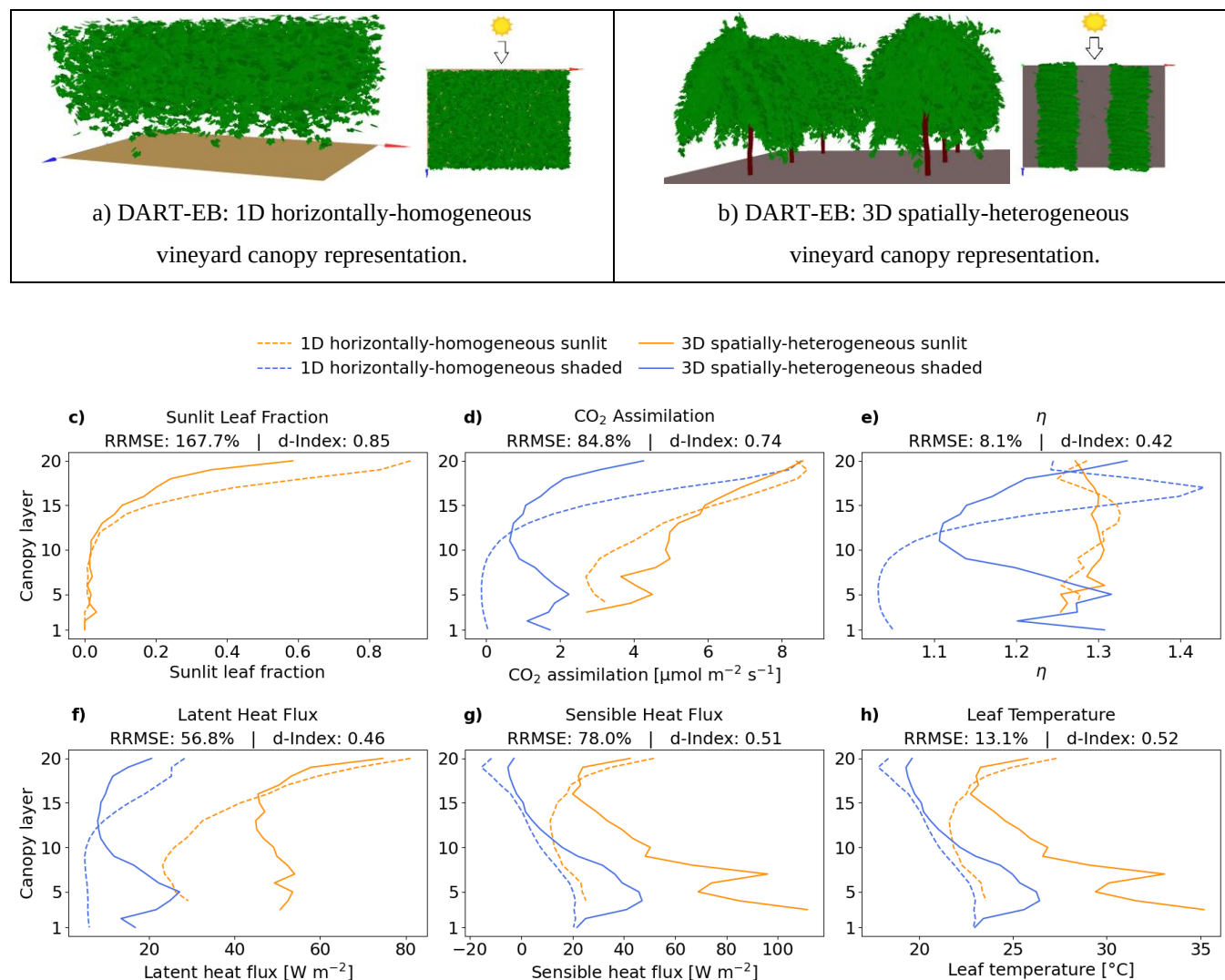


Figure 9: Vertical profiles of the (a) spatially-homogeneous and (b) geometrically-explicit vineyard scenes simulated in DART-EB. (c) Sunlit leaf fraction. (d) Net photosynthesis CO₂ assimilation. (e) η solar-induced fluorescence scaling factor. (f) Latent heat flux. (g) sensible heat flux. (h) Leaf temperature. For explanation of RRMSE and the similarity d-index see caption of Figure 6.

Figure 10 visualises the DART-EB per-facet simulated 3D distributions of net photosynthesis values, leaf temperatures, and the η fluorescence scaling factors for both vineyard representations. Uniformly distributed leaves of the horizontally-



homogeneous canopy representation resulted in the formation of distinct strata varying along the vertical axis. Conversely, the spatially-heterogeneous representation, which replicates the genuine 3D architecture of the vine shrubs, exhibits a non-uniform distribution characterized by distinct spherical foliage clusters. For instance, the 3D visualization of net photosynthesis (Fig. 10a) shows an outer-canopy cluster of sun-exposed leaves with high CO₂ assimilation rates and an interior cluster of foliage, receiving restricted solar illumination and, thus, yielding low CO₂ photosynthetic assimilation rates. Similar spatial patterns can be observed in 3D distributions of the η factors and leaf temperatures (Fig. 10b, c).

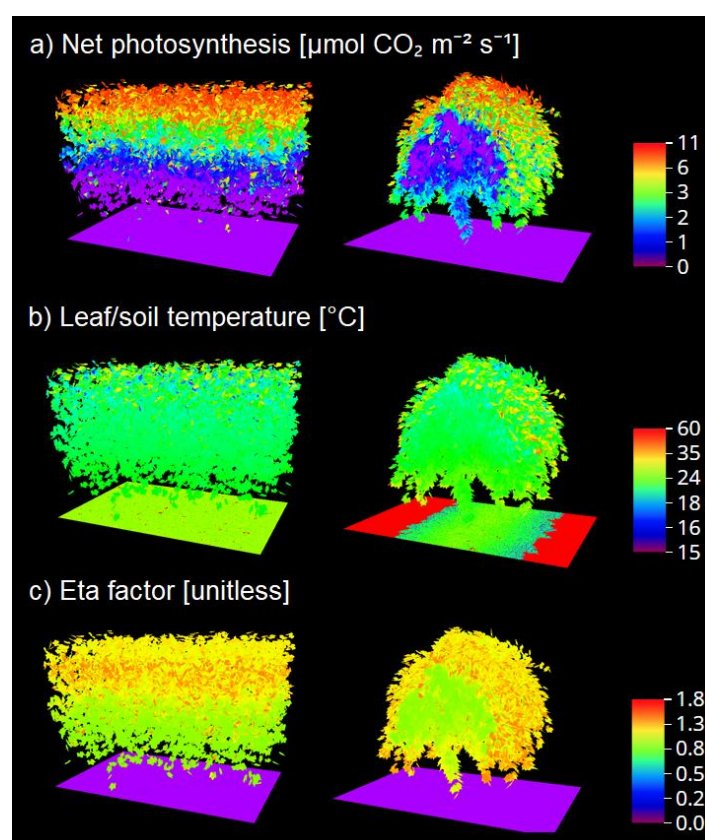


Figure 10: DART-EB 3D (a) net photosynthetic CO₂ assimilation, (b) leaf and soil temperature, and (c) η solar-induced fluorescence scaling factor for horizontally-homogeneous (left) and spatially-heterogeneous (right) geometrically-explicit vineyard canopies.

3.4 Comparison of DART-EB simulated and field measured alfalfa canopy physiological traits

The predictive performance of DART-EB was validated against in-situ field measurements acquired over an alfalfa canopy. Since stems were assumed to be photosynthetically inactive, non-transpiring, and contributing only to the sensible heat flux, the analyses focused on the foliage physiological outputs, specifically CO₂ assimilation, APAR_{chl}, and heat fluxes. In the case



of a realistically distributed foliage (i.e., heterogeneous canopy), the diurnal course of modelled net photosynthesis (A_n) exhibited a high agreement with the in-situ measurements (Fig. 11), with CO_2 assimilation rates increasing throughout the morning, reaching a maximum around 13:00 of local time (GMT +2), and steadily declining during the afternoon. Overall modelling error remained low (RRMSE of 8 %), with DART-EB A_n values falling within or very close to the uncertainty buffer of field-measurements, driven by a variation in actual soil respiration. In the second case of the homogeneous canopy structure, the simulated A_n was significantly higher than the field measurements across all time steps (RRMSE of 20 %). The main driver of this overestimation is the markedly increased total APAR_{chl} (Fig. 12). Interestingly, the diurnal courses of latent and sensible heat fluxes for both types of canopies revealed the same systematic deviations from the field-measured heat fluxes, i.e., overestimation for latent and underestimation for sensible heat flux (see Fig. 13).

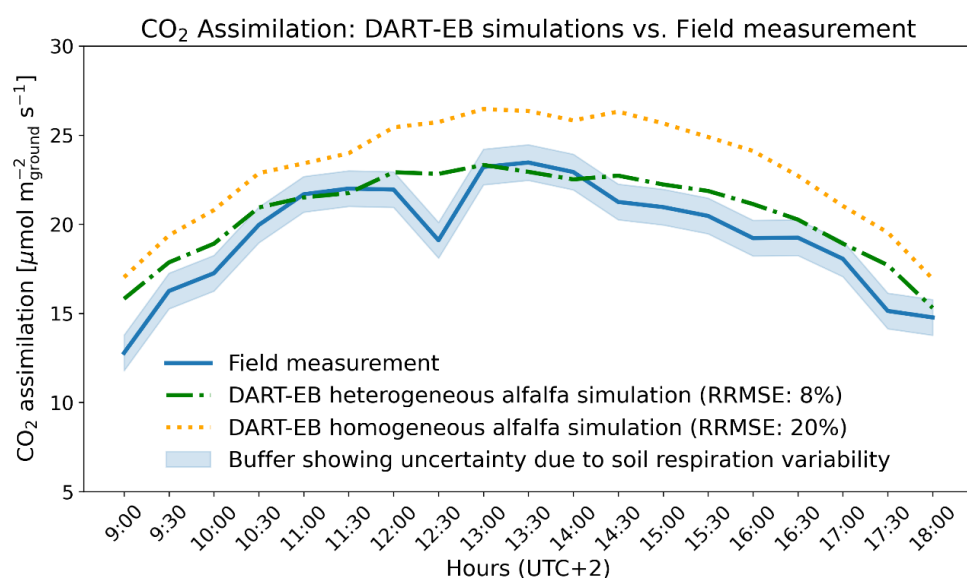


Figure 11: Validation of DART-EB simulated diurnal foliage net photosynthesis (A_n) against in-situ measurements July 17, 2021. The shaded blue buffer represents uncertainty due to actual soil respiration variability, gaining values of up to $4 \mu\text{mol CO}_2 \text{ m}^{-2} \text{ s}^{-1}$.

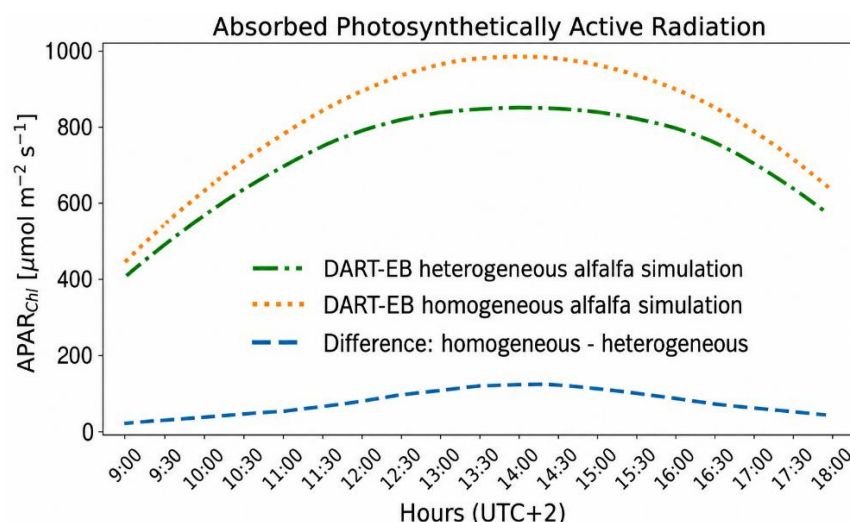


Figure 12: Impact of 3D structural representation of alfalfa canopy (i.e., spatially homogeneous vs. heterogeneous foliage distribution) on the diurnal course of total absorbed photosynthetically active radiation by leaf chlorophylls (APAR_{chl}).

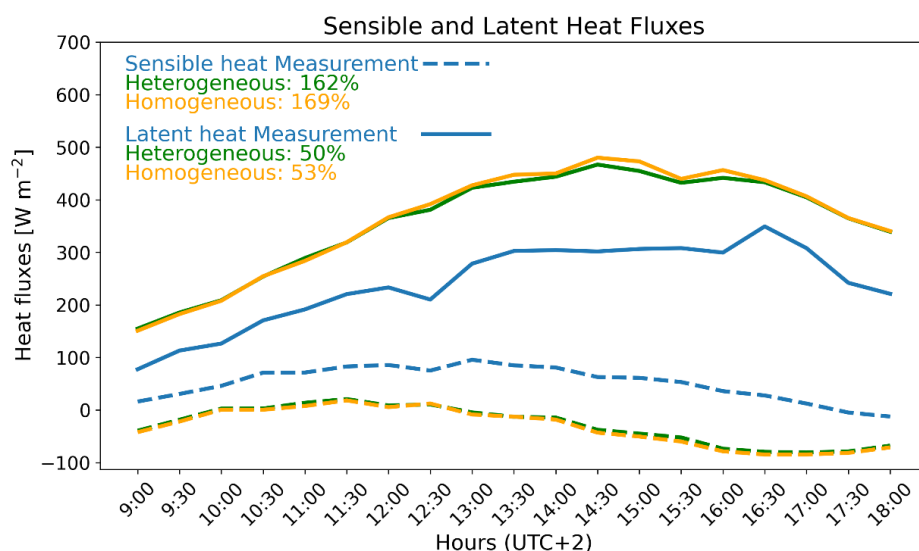


Figure 13: DART-EB simulated diurnal courses of latent (LE) and sensible (H) heat fluxes for spatially homogeneous and heterogeneous alfalfa canopies compared against field-measured heat fluxes. The relative (%) values indicate the RRMSE between the simulated heat fluxes and the corresponding field measurements.



4 Discussion

4.1 DART-EB modelling consistency in the case of spatially-homogeneous quasi-turbid canopy

The aim of this work was to develop a 3D energy balance model for vegetation canopies, resolving processes of photosynthesis, latent and sensible heat fluxes, and surface temperatures at the level of individual triangular facets representing plant leaves and bare soil ground surface. Results demonstrate not only the feasibility of such a modelling framework, capable of capturing spatiotemporal dynamics of vegetated ecosystems, but also advancements and accuracy improvements due to the geometrically explicit representation of 3D canopy structures. The validity of the facet-based approach is supported by a reciprocal consistency between DART-EB and SCOPE energy balance outputs. This was evidenced by high indices of agreement and low RRMSEs across primary physical and physiological outputs (e.g., the sunlit foliage fraction, the net photosynthesis, or the η factor), achieved for spatially homogeneous quasi-turbid canopy simulations. An exception was the sensible heat flux, for which the RRMSE was higher than expected due to some values close to zero.

Although DART-EB and SCOPE physiological variables showed, in general, a strong agreement and small overall modelling deviations, some moderate discrepancies were found in the middle and lower canopy layers for latent heat, sensible heat, and leaf temperature outputs. These minor variations are attributed to models' dissimilar treatments of direct and diffuse radiation fluxes and their subsequent absorption. Whereas SCOPE employs a four-stream directional radiation budget approximation, DART-Lux utilises a bi-directional Monte Carlo approach providing a more detailed assessment of 3D radiation budget within the simulated canopy.

Distinguishing between the physiological states of sunlit and shaded leaves is of a high importance for accurate simulation of a vegetation canopy SIF. By resolving the 3D energy balance at the level of individual leaf facets, DART-EB enables to adjust the pre-defined PSII fluorescence quantum efficiency (FQE) of dark-adapted leaves using the η correction factor computed for leaf-specific local microclimatic environmental conditions. This functionality allows DART-EB to simulate SIF of structurally heterogeneous canopies more accurately and, subsequently, provides a physically sound foundation for improved SIF-based GPP retrievals in structurally complex canopies.

4.2 Impact of spatial heterogeneity on canopy energy balance and physiology

To isolate and analyse the impact of 3D spatially-heterogeneous canopy structure, we simulated a virtual row-crop made by two columns of leaves maintaining the same total LAI and random distribution as the reference homogenous canopy (Fig. 7a, b). DART-EB results indicate that the spatial leaf arrangement and density are important determinants of the internal canopy radiation distribution and microclimate. The simple rearrangement of foliage distribution in denser columns, with no change in biomass amount, induced substantial changes in most modelled physiological and energy balance variables. The introduction of the horizontal clumping altered the internal canopy light environment, resulting in a lower fraction of sunlit leaves across all vertical canopy layers when compared to the homogeneous reference (Fig. 7c). This systematic shift indicates that the tested 1D turbid medium canopy abstraction misrepresented the light-harvesting potential of a clumped vegetation (Boitard et al.,



2023), as it failed to account for the increased internal foliage shadowing and canopy gaps that characterise row-crop architectures. This radiative discrepancy, causing miscalculation of leaf absorbed radiation and $APAR_{chl}$, propagated further in the simulated energy exchange and physiological processes. The most pronounced impact was observed in the energy balance variables, i.e., both heat fluxes and leaf temperature, which exhibited largest dissimilarities with the spatially-homogeneous case (Fig. 7f-h). A strong divergence was also observed for the SIF correction η factor, especially in the case of shaded foliage (Fig. 7e).

Building upon the simple theoretical simulations, we quantified the impact of horizontally as well as vertically heterogeneous foliage distribution, featured by a structurally diverse vineyard canopy mock-up. The results demonstrated how much limited is the 1D canopy representation without the foliage clumping in capturing the sun-illumination and internal shadowing patterns. The radiative divergence between the 3D spatially-heterogeneous and the 1D horizontally-homogeneous vine canopies was largest in their upper layers, where the 1D abstraction resulted in a substantially different ratio of sunlit and shaded leaves (Fig. 9c). Consequently, the 1D canopy representation overestimated severely $APAR_{chl}$ of foliage (Fig. 8). As the full 3D canopy representation accounts for foliage gaps and clumping in rows, it allowed direct radiation to reach the soil surface and produced less sunlit leaves in the upper canopy layers. As shown in Table 1, the resulting 48 % relative difference in $APAR_{chl}$ induced 44 % lower total net photosynthesis in the 3D spatially-heterogeneous vineyard. To conclude, our results demonstrate that the explicit 3D modelling is required to simulate intricate leaf-photon interactions and internal canopy shadowing that cannot be captured by 1D canopy abstractions. Additionally, canopy gaps in the geometrically-explicit 3D heterogeneous vineyard allowed direct solar radiation to reach the ground, creating localised thermal sun-flecks, whereas the horizontally-homogeneous foliage caused overestimation of soil shading, resulting in unnaturally low soil temperatures.

The visualisations of 3D spatial distributions of the two vineyards simulated net photosynthesis, leaf soil temperature, and η SIF factors (Fig. 10) illustrate the influence of the 3D canopy structure. Although these 3D maps can localize quantitative systematic biases between 3D and 1D approaches, they lack a direct field validation. The accuracy assessment of these outputs against vineyard in-situ measurements is required before deploying the DART-EB 3D modelling in practical precision agriculture applications.

4.3 Validation of DART-EB modelled outputs against in-situ alfalfa measurements

The successful validation of DART-EB outputs against in-situ alfalfa field measurements demonstrates its high predictive potential for realistic, high-resolution vegetation architectures. The high degree of correspondence between the diurnal courses of net photosynthesis A_n rates (Fig. 11) and a RRMSE of 8 % indicate that a 3D plant representation is essential for an accurate modelling of CO_2 assimilation in agricultural crops, particularly during their early growth stages when canopy gaps and a contribution of soil background play an important role. When the alfalfa canopy was represented by a homogeneous abstraction, the modelling error increased significantly (RRMSE of 20 %) despite using identical biochemical and biophysical parameterisation. This error increase was caused by a uniform horizontal foliage distribution, inducing an unrealistically high canopy PAR interception (Fig. 12). An additional factor, driving the substantial discrepancy in A_n rates between alfalfa



homogeneous and heterogeneous simulations, was the exceptionally high mean V_{cmax} value of $215 \mu\text{mol m}^{-2} \text{s}^{-1}$. Since an elevated carboxylation capacity increases the sensitivity of carbon assimilation to light availability, even a small overestimation in APAR_{chl} induces a significant offset in the resulting A_n rates. Additional discrepancies regarding the energy exchange were found for the homogeneous as well as heterogeneous alfalfa representations. Although both simulations produced almost identical quantifications of sensible and latent heat fluxes, they both deviated notably from in-situ measurements (Fig. 13). This systematic uncertainty is attributed to the underperforming aerodynamic resistance module that does not account for dynamic 3D wind fields nor for row-orientation-driven turbulence. Addressing these limitations is a primary focus of the next DART-EB development.

Although researchers have previously documented stem-level CO_2 assimilation for some members of the *Fabaceae* family, e.g., *Spartium* species (Nilsen, 1992; Aschan and Pfanz, 2003), specific physiological data for the *Medicago* genus were not found. Consequently, we assumed that only the leaf cohort contributed to the latent heat flux and carbon assimilation, while the stems were considered as non-transpiring elements contributing exclusively to the sensible heat flux. While the thin stems of alfalfa represent a negligible heat storage, the application of DART-EB on woody species, e.g., fruit-tree orchards or forests, will require resolving the thermal inertia of large-sized trunks. Furthermore, moving from a mono-species crop to a multi-species forest will necessitate accounting for the distinct physiological signatures of the understory and the complex light-harvesting dynamics of varying tree overstory plant types. Adjusting and validating DART-EB for these complex environments will be a critical step towards inclusion of microclimatic drivers in modelling terrestrial carbon cycle and GPP predictions.

4.4 Current model performance and limitations

Resolving physiological and energy balance processes at the level of individual triangular facets allows DART-EB to provide high-resolution maps at the leaf scale. This structural realism of DART-EB necessitates a computational trade-off. While a single run of a 1D model, such as SCOPE, takes tens of seconds, a DART-EB calculation can take up to one hour on a standard laptop/desktop computer, required to process millions of facets. Another limitation is represented by the actual aerodynamic resistance module, which assumes 1D canopy horizontal homogeneity and utilises only a wind speed without accounting for a wind directionality. Neglecting the 3D wind field in row-crop systems naturally oversimplifies modelling of an airflow friction and local velocity, and subsequently impacts the partitioning of heat fluxes. Finally, although DART-EB is one of the first adopters of the new Johnson-Berry photosynthesis model, allowing for more mechanistic simulations of photosynthetic processes and SIF fluxes, its validation is still pending, hindered by the scarcity of concurrent photosystem-level parametrisation measurements that would explicitly account for a 3D architecture of modelled plant canopies.

5 Conclusion

In this study, we demonstrated the design, functionality, and performance of DART-EB, a 3D soil–plant–atmosphere energy balance model created by coupling the DART radiative transfer with spatially-explicit simulations of ecosystem energy



exchange. A central innovation of DART-EB is the implementation of multiple models for photosynthesis, energy balance, latent and sensible heat fluxes, aerodynamic resistance, and soil heat storage per individual triangular facet that can represent either plant leaves or soil surfaces. The structurally detailed and discrete geometrical representation of plants makes DART-EB a physically robust framework for capturing the microclimatic heterogeneity within even complex canopy structures. The model's physical consistency was confirmed through output agreements with the well-established and validated 1D SCOPE model (Yang et al., 2020). When simulating comparable spatially homogeneous canopy representations, SCOPE and DART-EB yielded high agreements ($d \geq 0.96$) in vertical canopy profiles of all primary physical and physiological outputs (i.e., net photosynthesis, the η SIF correction factor, sensible and latent heat fluxes, as well as leaf surface temperature). Our DART-EB simulation of a realistic 3D vineyard revealed that 1D canopy abstractions can artificially inflate PAR interception, leading to substantial inaccuracies, as, for instance, a 44 % overestimation of the net photosynthetic CO_2 assimilation rate. Our findings emphasize that a leaf physiological state cannot be accurately modelled just based on its height in the canopy vertical profile. High accuracy requires additional geometrical information on foliage 3D canopy positioning and dimensions that encompasses actual leaf size, density, angularity and clumping. The DART-EB performance reliability was demonstrated by its ability to reproduce the diurnal course of net photosynthetic CO_2 assimilation for a real alfalfa crop, achieving 8 % relative root mean square error against field measurements. This robust predictive performance resulted from an accurate modelling of APAR_{chl} , enabled by the geometrically-explicit 3D distribution of foliage facets. By resolving leaf physiological states under varying environmental conditions at the level of individual facet, DART-EB offers a new capability for ecological modelling research and remote sensing applications of vegetated ecosystems at detailed spatial scales, for example, a SIF-based high-resolution GPP canopy mapping.

Appendix A. Conversion of radiant flux density units from W m^{-2} to $\mu\text{mol photon m}^{-2} \text{s}^{-1}$

Biochemical photosynthesis models require the absorption of photosynthetically active radiation between 400 and 780 nm by chlorophyll (APAR_{chl}), here denoted as $E_{\text{APAR}}^{\text{chl}}$, which is expressed in Photosynthetic Photon Flux Density (PPFD, $\mu\text{mol m}^{-2} \text{s}^{-1}$). As the energy of a photon depends on its wavelength, the conversion of an absorbed radiation from Watts to photon flux ($\mu\text{mol s}^{-1}$) uses a set of conversion factors ($\mu_{\text{abs}}^{\text{chl}}$). The absorption coefficient for chlorophyll, relative to the total absorption by all vegetation constituents at a given wavelength λ , is $K_{\text{abs}}^{\text{chl}}(\lambda) = \frac{K_{\text{abs}}^{\text{chl}}(\lambda)}{K_{\text{abs}}^{\text{tot}}(\lambda)}$, where K represents the specific absorption coefficients for different vegetation traits, including chlorophyll $a+b$, total carotenoids, and anthocyanins. These K values can be extracted from the Optipar table in the fluspect_parameters folder of the SCOPE GitHub repository. $K_{\text{abs}}^{\text{tot}}(\lambda)$ denotes the sum of the absorption coefficients for all vegetation components. For a spectral band $\Delta\lambda_i$, the conversion factor is:

$$\mu_{\text{abs}, \Delta\lambda_i}^{\text{chl}} = \frac{10^6}{h.c.N_a} \cdot \frac{\int_{\Delta\lambda_i} K_{\text{abs}}^{\text{chl}}(\lambda) \cdot L_B(\lambda, T) \cdot \lambda \cdot [1 - \omega_l(\lambda)] \cdot d\lambda}{\int_{\Delta\lambda_i} L_B(\lambda, T) \cdot [1 - \omega_l(\lambda)] \cdot d\lambda},$$



where T is the temperature of the sun surface (i.e., 5777 K), c is the speed of light in vacuum (299,792,458 m s⁻¹), h is the Planck's constant (6.62618·10⁻³⁴ J s⁻¹), N_a is the Avogadro's constant (6.02214076·10²³), $\omega_l(\lambda)$ is the sum of facet reflectance and transmittance at a given wavelength λ , and L_B is the Planck's law for a blackbody radiation.

$\mu_{abs,\Delta\lambda_i}^{chl}$ is used to derive the absorbed photon flux in $\mu\text{mol m}^{-2} \text{s}^{-1}$ from the total absorbed flux in W m^{-2} :

$$E_{abs,\Delta\lambda_i}^{chl} (\mu\text{mol m}^{-2} \text{s}^{-1}) = \mu_{abs,\Delta\lambda_i}^{chl} \cdot E_{abs,\Delta\lambda_i}^{total} (\text{W m}^{-2}).$$

The total APAR_{chl} flux is a sum over all the spectral bands $\Delta\lambda_i$:

$$E_{APAR}^{chl} (\mu\text{mol m}^{-2} \text{s}^{-1}) = \sum_{i=1}^I \mu_{abs,\Delta\lambda_i}^{chl} \cdot E_{abs,\Delta\lambda_i}^{total} (\text{W m}^{-2}),$$

Appendix B. Energy Balance Components

Net radiation R is calculated as the absorbed radiation minus the emitted radiation by a given leaf facet i for the wavelengths from 0.4 μm to 50 μm . λE and H are computed as follows:

$$R = \text{Absorption} - \text{Emission},$$

$$H = \rho_a c_p \frac{T_i - T_{air}}{ar_i},$$

$$L \cdot E = L \cdot \frac{q_i(T_i) - q_{air}}{ar_i - r_i},$$

where ρ_a is the air density (kg m⁻³), c_p is the specific heat capacity of air (J kg⁻¹ K⁻¹), L is the latent heat of water vaporization (J kg⁻¹), T_i is the temperature of the facet (°C), T_{air} is the air temperature above the canopy (°C), $q_i(T_i)$ is the specific humidity at the temperature T_i in stomata (for a leaf facet) or within soil pores (for a soil facet) (kg m⁻³), q_{air} is the specific humidity above the canopy (kg m⁻³), ar_i is the aerodynamic resistance (s m⁻¹), and r_i is the stomatal resistance (for leaf facet) or the soil surface resistance (for soil facet) (s m⁻¹).

Temperature adjustments for each triangular element are performed using the Newton's method (Yang et al., 2020):

$$T_{after} = T_{before} + \frac{\text{error balance}}{\frac{\delta \text{error balance}}{\delta T}}.$$

Appendix C. Geometric classification of sunlit and shaded foliage facets

A classification, implemented in DART-Lux by Regaieg et al. (2023), classifies facets as either sunlit or shaded. First, a regular 3D grid is introduced in the simulated scene to spatially segment each facet. Two situations are possible:

- The facet is entirely enclosed within a single grid cell. Then, its centroid point P is assigned, and the local sunlit fraction

f_{sunlit} is calculated as the ratio of the incoming direct solar irradiance $E_{P,direct\ sun}$ at point P , considering the occlusion



by other scene elements, to the hypothetical irradiance $E_{P,sunlit}$ that P would receive assuming no obstacle between it and the sun (i.e., fully sunlit condition):

$$f_{sunlit} = \frac{E_{P,direct\ sun}}{E_{P,sunlit}}$$

where $E_{P,sunlit} = \frac{E_{BOA,sun}}{\cos(\theta_{sun})} \cdot |\Omega_{sun} \cdot \Omega_{leaf}|$, $E_{BOA,sun}$ is the direct bottom-of-atmosphere solar irradiance, θ_{sun} is the sun zenith angle, Ω_{sun} is the solar direction unit vector, and Ω_{leaf} is the leaf zenith angle.

- The facet is in several grid cells. Then, it is segmented into N sub-polygons and N centroid points (1 per sub-polygon) are calculated. The total sunlit fraction of the original facet is then derived as an area-weighted average of the sub-polygons' sunlit fractions.

A threshold of the f_{sunlit} variable, separating sunlit and shaded facets, is then applied to create a 3D mask of a sunlit fraction, hereafter referred to as sf_mask . Figure C1 shows the density distributions of the sunlit fraction for three different triangular facet sizes (i.e., 30, 10, and 5 cm²). The distribution of f_{sunlit} per facet is getting more bimodal as the facets become smaller, demonstrating that the sunlit fraction tends to accumulate around the minimum and maximum extremes. Since shaded facets should not receive any direct sunlight, the effect of direct solar radiation on facets classified as shaded is expected to be minimized during the threshold optimization. This requirement can be, however, overly restrictive with respect to some facet sizes. Considering these aspects, we set the default sunlit threshold sf_mask at 0.01 (1 %), as it minimizes the influence of direct sunlight on shaded facets and simultaneously maintains a sufficient density of shaded leaf facets, especially in cases of relatively large triangles.

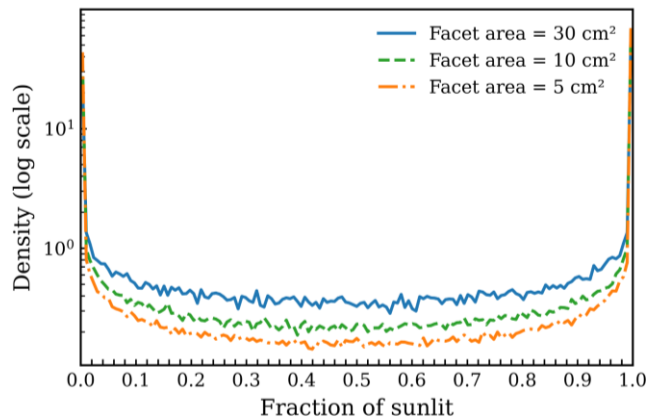


Figure C1: Fraction of leaf facet area receiving direct sun irradiance for three predefined facet-area sizes.



Appendix D. Index of agreement between two datasets

The d-index of agreement (Willmott, 1981) is a normalized statistical measure that quantifies the degree of correspondence (similarity) between two datasets, where one serves as the reference and the other is the examined dataset. It ranges from 0 to 1, with $d = 1$ indicating perfect agreement and $d = 0$ signifying no agreement. The formula for the d-index is:

$$d = 1 - \frac{\sum_{i=1}^n (E_i - R_i)^2}{\sum_{i=1}^n (|E_i - \bar{R}| + |R_i - \bar{R}|)^2},$$

where E_i represents the examined dataset values, R_i corresponds to the reference dataset values, $\bar{R}$ is the mean of the reference dataset, and n is the total number of observations.

The relative root mean square error (RRMSE) was calculated as:

$$RRMSE = 100 \times \frac{\sqrt{\frac{1}{n} \sum_{i=1}^n (E_i - R_i)^2}}{\bar{R}}.$$

Code and data availability

Raw data and the DART-EB python code used in this study can be provided by the corresponding authors upon request.

Author contributions

Thắng Quang Nguyễn: Conceptualization, Methodology, Software, Data curation, Investigation, Formal analysis, Validation, Visualization, Writing (original draft preparation). **Luka Lesage:** Software, Visualization, Writing (original draft preparation). **Omar Regaieg:** Resources, Software, Writing (review and editing). **Jean-Philippe Gastellu-Etchegorry** and **Zbyněk Malenovský:** Funding acquisition, Project administration, Conceptualization, Methodology, Supervision, Writing (review and editing).

Competing interests

The corresponding author declared that none of the authors has any competing interests.

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References

- Anav, A., Friedlingstein, P., Beer, C., Ciais, P., Harper, A., Jones, C., Murray-Tortarolo, G., Papale, D., Parazoo, N. C., Peylin, P., Piao, S., Sitch, S., Viovy, N., Wiltshire, A., and Zhao, M.: Spatiotemporal patterns of terrestrial gross primary production: A review: GPP Spatiotemporal Patterns, *Rev. Geophys.*, 53, 785–818, <https://doi.org/10.1002/2015RG000483>, 2015.
- Aschan, G. and Pfanz, H.: Non-foliar photosynthesis – a strategy of additional carbon acquisition, *Flora - Morphology, Distribution, Functional Ecology of Plants*, 198, 81–97, <https://doi.org/10.1078/0367-2530-00080>, 2003.
- Bablt, A., Vu, P. V. H., Jacquemoud, S., Viallefont-Robinet, F., Fabre, S., Briottet, X., Sadeghi, M., Whiting, M. L., Baret, F., and Tian, J.: MARMIT: A multilayer radiative transfer model of soil reflectance to estimate surface soil moisture content in the solar domain (400–2500 nm), *Remote Sensing of Environment*, 217, 1–17, <https://doi.org/10.1016/j.rse.2018.07.031>, 2018.
- Bailey, B. N.: Helios: A Scalable 3D Plant and Environmental Biophysical Modeling Framework, *Front. Plant Sci.*, 10, 1185, <https://doi.org/10.3389/fpls.2019.01185>, 2019.
- Ball, J. T., Woodrow, I. E., and Berry, J. A.: A Model Predicting Stomatal Conductance and its Contribution to the Control of Photosynthesis under Different Environmental Conditions, in: *Progress in Photosynthesis Research*, edited by: Biggins, J., Springer Netherlands, Dordrecht, 221–224, https://doi.org/10.1007/978-94-017-0519-6_48, 1987.
- Béland, M., Bonan, G. B., Meyers, T. P., Munger, J. W., Kobayashi, H., and Baldocchi, D.: Advances in Modelling Radiative Transfer, Heat Storage and Turbulent Transport to Evaluate CO₂, Heat and Water Fluxes Over Broad-Leaved Forests: The CANVEG2 Model, *Global Change Biology*, 32, e70867, <https://doi.org/10.1111/gcb.70867>, 2026.
- Boitard, P., Coudert, B., Lauret, N., Queguiner, S., Marais-Sicre, C., Regaieg, O., Wang, Y., and Gastellu-Etchegorry, J.-P.: Calibration of DART 3D model with UAV and Sentinel-2 for studying the radiative budget of conventional and agro-ecological maize fields, *Remote Sensing Applications: Society and Environment*, 32, 101079, <https://doi.org/10.1016/j.rsase.2023.101079>, 2023.
- Branch, O., Martinez Villagrasa, D., Mangan, M. R., Hartogensis, O., Boone, A., Branch, O., Canut, G., Cuxart, J., de Boar, H., Le Page, M., Miro, J. R., and Price, J.: LIAISE_UNIFIED-EC_WUR_30min_L1, <https://doi.org/10.25326/390>, 2022.
- Brent, R. P.: An algorithm with guaranteed convergence for finding a zero of a function, *The Computer Journal*, 14, 422–425, <https://doi.org/10.1093/comjnl/14.4.422>, 1971.
- Christiaan van der Tol, Berry, J. A., Campbell, P. K. E., and Rascher, U.: Models of fluorescence and photosynthesis for interpreting measurements of solar-induced chlorophyll fluorescence, *J. Geophys. Res. Biogeosci.*, 119, 2312–2327, <https://doi.org/10.1002/2014JG002713>, 2014.
- Collatz, G. J., Ball, J. T., Grivet, C., and Berry, J. A.: Physiological and environmental regulation of stomatal conductance, photosynthesis and transpiration: a model that includes a laminar boundary layer, *Agricultural and Forest Meteorology*, 54, 107–136, [https://doi.org/10.1016/0168-1923\(91\)90002-8](https://doi.org/10.1016/0168-1923(91)90002-8), 1991.



- 614 Farquhar, G. and Wong, S.: An Empirical Model of Stomatal Conductance, *Functional Plant Biol.*, 11, 191,
615 <https://doi.org/10.1071/PP9840191>, 1984.
- 616 Farquhar, G. D., Von Caemmerer, S., and Berry, J. A.: A biochemical model of photosynthetic CO₂ assimilation in leaves of
617 C₃ species, *Planta*, 149, 78–90, <https://doi.org/10.1007/BF00386231>, 1980.
- 618 Féret, J.-B., Berger, K., De Boissieu, F., and Malenovský, Z.: PROSPECT-PRO for estimating content of nitrogen-
619 containing leaf proteins and other carbon-based constituents, *Remote Sensing of Environment*, 252, 112173,
620 <https://doi.org/10.1016/j.rse.2020.112173>, 2021.
- 621 Galedar, M. N., Tabatabaeefar, A., Jafari, A., Sharifi, A., and Rafiee, S.: Bending and Shearing Characteristics of Alfalfa
622 Stems, n.d.
- 623 Gastellu-Etchegorry, J. P., Demarez, V., Pinel, V., and Zagolski, F.: Modeling Radiative Transfer in Heterogeneous 3-D
624 Vegetation Canopies, 1996.
- 625 Gastellu-Etchegorry, J.-P., Yin, T., Lauret, N., Cajgfinger, T., Gregoire, T., Grau, E., Feret, J.-B., Lopes, M., Guilleux, J.,
626 Dedieu, G., Malenovský, Z., Cook, B. D., Morton, D., Rubio, J., Durrieu, S., Cazanave, G., Martin, E., and Ristorcelli, T.:
627 Discrete Anisotropic Radiative Transfer (DART 5) for Modeling Airborne and Satellite Spectroradiometer and LIDAR
628 Acquisitions of Natural and Urban Landscapes, *Remote Sensing*, 7, 1667–1701, <https://doi.org/10.3390/rs70201667>, 2015.
- 629 González-Armas, R., Vilà-Guerau De Arellano, J., Mangan, M. R., Hartogensis, O., and De Boer, H.: Impact of canopy
630 environmental variables on the diurnal dynamics of water and carbon dioxide exchange at leaf and canopy level,
631 *Biogeosciences*, 21, 2425–2445, <https://doi.org/10.5194/bg-21-2425-2024>, 2024.
- 632 Jacquemoud, S. and Baret, F.: PROSPECT: A model of leaf optical properties spectra, *Remote Sensing of Environment*, 34,
633 75–91, [https://doi.org/10.1016/0034-4257\(90\)90100-Z](https://doi.org/10.1016/0034-4257(90)90100-Z), 1990.
- 634 Johnson, J. E. and Berry, J. A.: The role of Cytochrome b₆f in the control of steady-state photosynthesis: a conceptual and
635 quantitative model, *Photosynth Res*, 148, 101–136, <https://doi.org/10.1007/s11120-021-00840-4>, 2021.
- 636 Johnson, J. E., Field, C. B., and Berry, J. A.: The limiting factors and regulatory processes that control the environmental
637 responses of C₃, C₃–C₄ intermediate, and C₄ photosynthesis, *Oecologia*, 197, 841–866, [https://doi.org/10.1007/s00442-021-](https://doi.org/10.1007/s00442-021-05062-y)
638 05062-y, 2021.
- 639 Knyazikhin, Y. and Marshak, A.: Fundamental Equations of Radiative Transfer in Leaf Canopies, and Iterative Methods for
640 Their Solution, in: *Photon-Vegetation Interactions*, edited by: Myneni, R. B. and Ross, J., Springer Berlin Heidelberg,
641 Berlin, Heidelberg, 9–43, https://doi.org/10.1007/978-3-642-75389-3_2, 1991.
- 642 Kobayashi, H. and Iwabuchi, H.: A coupled 1-D atmosphere and 3-D canopy radiative transfer model for canopy reflectance,
643 light environment, and photosynthesis simulation in a heterogeneous landscape, *Remote Sensing of Environment*, 112, 173–
644 185, <https://doi.org/10.1016/j.rse.2007.04.010>, 2008.
- 645 Kobayashi, H., Baldocchi, D. D., Ryu, Y., Chen, Q., Ma, S., Osuna, J. L., and Ustin, S. L.: Modeling energy and carbon
646 fluxes in a heterogeneous oak woodland: A three-dimensional approach, *Agricultural and Forest Meteorology*, 152, 83–100,
647 <https://doi.org/10.1016/j.agrformet.2011.09.008>, 2012.
- 648 Malenovský, Z., Regaieg, O., Yin, T., Lauret, N., Guilleux, J., Chavanon, E., Duran, N., Janoutová, R., Delavois, A.,
649 Meynier, J., Medjdoub, G., Yang, P., Van Der Tol, C., Morton, D., Cook, B. D., and Gastellu-Etchegorry, J.-P.: Discrete



- 650 anisotropic radiative transfer modelling of solar-induced chlorophyll fluorescence: Structural impacts in geometrically
651 explicit vegetation canopies, *Remote Sensing of Environment*, 263, 112564, <https://doi.org/10.1016/j.rse.2021.112564>, 2021.
- 652 Meyers, T.: An assessment of storage terms in the surface energy balance of maize and soybean, *Agricultural and Forest*
653 *Meteorology*, 125, 105–115, <https://doi.org/10.1016/j.agrformet.2004.03.001>, 2004.
- 654 Nilsen, E. T.: The influence of water stress on leaf and stem photosynthesis in *Spartium junceum* L., *Plant Cell &*
655 *Environment*, 15, 455–461, <https://doi.org/10.1111/j.1365-3040.1992.tb00996.x>, 1992.
- 656 Prikaziuk, E., Migliavacca, M., Su, Z. (Bob), and Van Der Tol, C.: Simulation of ecosystem fluxes with the SCOPE model:
657 Sensitivity to parametrization and evaluation with flux tower observations, *Remote Sensing of Environment*, 284, 113324,
658 <https://doi.org/10.1016/j.rse.2022.113324>, 2023.
- 659 Regaieg, O.: Modeling radiative transfer of Sun-Induced Fluorescence, thermal emission and radiative budget of 3D
660 vegetation canopies : towards a comprehensive 3D SIF model, Theses, Université Paul Sabatier - Toulouse III,
661 <https://doi.org/10.70675/d2c9a032zc3e5z4eaezae5bzcada79f3bddd>, 2023.
- 662 Regaieg, O., Lauret, N., Wang, Y., Guilleux, J., Chavanon, E., and Gastellu-Etchegorry, J.-P.: Bi-directional Monte-Carlo
663 modelling of solar-induced chlorophyll fluorescence images for 3D vegetation canopies in the DART model, *International*
664 *Journal of Applied Earth Observation and Geoinformation*, 118, 103254, <https://doi.org/10.1016/j.jag.2023.103254>, 2023.
- 665 Regaieg, O., Malenovský, Z., Siegmann, B., Buffat, J., Krämer, J., Lauret, N., and Le Dantec, V.: DART-based temporal and
666 spatial retrievals of solar-induced chlorophyll fluorescence quantum efficiency from in-situ and airborne crop observations,
667 *Remote Sensing of Environment*, 319, 114636, <https://doi.org/10.1016/j.rse.2025.114636>, 2025.
- 668 Sakai, Y., Kobayashi, H., and Kato, T.: FLiES-SIF version 1.0: three-dimensional radiative transfer model for estimating
669 solar induced fluorescence, *Geosci. Model Dev.*, 13, 4041–4066, <https://doi.org/10.5194/gmd-13-4041-2020>, 2020.
- 670 Sellers, P. J., Randall, D. A., Collatz, G. J., Berry, J. A., Field, C. B., Dazlich, D. A., Zhang, C., Collelo, G. D., and
671 Bounoua, L.: A Revised Land Surface Parameterization (SiB2) for Atmospheric GCMS. Part I: Model Formulation, *J.*
672 *Climate*, 9, 676–705, [https://doi.org/10.1175/1520-0442\(1996\)009%3C0676:ARLSPF%3E2.0.CO;2](https://doi.org/10.1175/1520-0442(1996)009%3C0676:ARLSPF%3E2.0.CO;2), 1996.
- 673 Van Der Tol, C., Verhoef, W., Timmermans, J., Verhoef, A., and Su, Z.: An integrated model of soil-canopy spectral
674 radiances, photosynthesis, fluorescence, temperature and energy balance, *Biogeosciences*, 6, 3109–3129,
675 <https://doi.org/10.5194/bg-6-3109-2009>, 2009.
- 676 Verhoef, A., McNaughton, K. G., and Jacobs, A. F. G.: A parameterization of momentum roughness length and
677 displacement height for a wide range of canopy densities, *Hydrol. Earth Syst. Sci.*, 1, 81–91, <https://doi.org/10.5194/hess-1-81-1997>, 1997.
- 679 Verhoef, W.: Light scattering by leaf layers with application to canopy reflectance modeling: The SAIL model, *Remote*
680 *Sensing of Environment*, 16, 125–141, [https://doi.org/10.1016/0034-4257\(84\)90057-9](https://doi.org/10.1016/0034-4257(84)90057-9), 1984.
- 681 Vilfan, N., Van Der Tol, C., Muller, O., Rascher, U., and Verhoef, W.: Fluspect-B: A model for leaf fluorescence,
682 reflectance and transmittance spectra, *Remote Sensing of Environment*, 186, 596–615,
683 <https://doi.org/10.1016/j.rse.2016.09.017>, 2016.
- 684 Vilfan, N., Van Der Tol, C., Yang, P., Wyber, R., Malenovský, Z., Robinson, S. A., and Verhoef, W.: Extending Fluspect to
685 simulate xanthophyll driven leaf reflectance dynamics, *Remote Sensing of Environment*, 211, 345–356,
686 <https://doi.org/10.1016/j.rse.2018.04.012>, 2018.



- 687 Von Caemmerer, S.: Biochemical Models of Leaf Photosynthesis, CSIRO Publishing,
688 <https://doi.org/10.1071/9780643103405>, 2000.
- 689 Von Caemmerer, S.: Steady-state models of photosynthesis: Steady-state models of photosynthesis, *Plant Cell Environ*, 36,
690 1617–1630, <https://doi.org/10.1111/pce.12098>, 2013.
- 691 Von Caemmerer, S. and Farquhar, G. D.: Some relationships between the biochemistry of photosynthesis and the gas
692 exchange of leaves, *Planta*, 153, 376–387, <https://doi.org/10.1007/BF00384257>, 1981.
- 693 Wallace, Verhoef, and Anne: Modelling interactions in mixed-plant communities: light, water and carbon dioxide. In: *Leaf
694 development and canopy growth.*, 2000.
- 695 Wang, X., Guan, K., Wang, S., Bailey, B. N., Ainsworth, E. A., Jiang, Z., and Li, K.: Impact of vertical and seasonal
696 variation in leaf traits on simulating soybean canopy photosynthesis via 1D and 3D modeling, *Agricultural and Forest
697 Meteorology*, 377, 110941, <https://doi.org/10.1016/j.agrformet.2025.110941>, 2026.
- 698 Wang, Y., Kallel, A., Yang, X., Regaieg, O., Lauret, N., Guilleux, J., Chavanon, E., and Gastellu-Etchegorry, J.-P.: DART-
699 Lux: An unbiased and rapid Monte Carlo radiative transfer method for simulating remote sensing images, *Remote Sensing of
700 Environment*, 274, 112973, <https://doi.org/10.1016/j.rse.2022.112973>, 2022.
- 701 Willmott, C. J.: ON THE VALIDATION OF MODELS, *Physical Geography*, 2, 184–194,
702 <https://doi.org/10.1080/02723646.1981.10642213>, 1981.
- 703 Wynaendts, S.: The impact of the photosynthetic traits' downregulation on the leaf nutrient composition, Utrecht University
704 Repository, <https://studenttheses.uu.nl/handle/20.500.12932/42287>, 2022.
- 705 Xu, K., Yang, W., and Ye, H.: Thermal infrared reflectance characteristics of natural leaves in 8–14 μm region: Mechanistic
706 modeling and relationships with leaf water content, *Remote Sensing of Environment*, 294, 113631,
707 <https://doi.org/10.1016/j.rse.2023.113631>, 2023.
- 708 Yang, P., Prikaziuk, E., Verhoef, W., and Van Der Tol, C.: SCOPE 2.0: A model to simulate vegetated land surface fluxes
709 and satellite signals, *Biogeosciences*, <https://doi.org/10.5194/gmd-2020-251>, 2020.
- 710 Yin, T., Gastellu-Etchegorry, J.-P., Lauret, N., Grau, E., and Rubio, J.: A new approach of direction discretization and
711 oversampling for 3D anisotropic radiative transfer modeling, *Remote Sensing of Environment*, 135, 213–223,
712 <https://doi.org/10.1016/j.rse.2013.03.030>, 2013.
- 713 Yin, T., Lauret, N., and Gastellu-Etchegorry, J.-P.: Simulating images of passive sensors with finite field of view by
714 coupling 3-D radiative transfer model and sensor perspective projection, *Remote Sensing of Environment*, 162, 169–185,
715 <https://doi.org/10.1016/j.rse.2015.02.020>, 2015.
- 716 Zhao, F., Li, Z., Verhoef, W., Fan, C., Luan, H., Yin, T., Zhang, J., Liu, Z., Tong, C., and Bao, Y.: Simulation of solar-
717 induced chlorophyll fluorescence by modeling radiative coupling between vegetation and atmosphere with WPS, *Remote
718 Sensing of Environment*, 277, 113075, <https://doi.org/10.1016/j.rse.2022.113075>, 2022.
- 719 Wynaendts, S.: The impact of the photosynthetic traits' downregulation on the leaf nutrient composition, Utrecht University
720 Repository, <https://studenttheses.uu.nl/handle/20.500.12932/42287>, 2022.