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Research Progress and Applications of Three-Dimensional Computer Simulation Models in Optical Remote Sensing

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Abstract:

Three-dimensional (3D) computer simulation models are crucial components in studying remote sensing radiation transmission mechanisms, playing a significant role in forward modeling of complex surfaces and remote sensing inversion. Over the past two decades, remarkable progress has been made in 3D computer modeling research, with widespread applications in analyzing surface radiation transmission processes, validating models and algorithms, and remote sensing inversion. To fully understand the development of 3D computer simulation models, explore the differences between models, and discuss how to better apply them to daily life and production, this paper provides a comprehensive overview of 3D computer simulation models in optical remote sensing. The discussion is structured around three main aspects: model principles, applications, and development trends. Firstly, the principles of ray tracing and radiosity methods, along with existing models, are briefly introduced. Secondly, the primary applications of 3D computer simulation models in remote sensing are summarized. Finally, the future development trends of these models are discussed, analyzing the trends in 3D computer simulation model development and remote sensing applications based on issues and needs related to operational efficiency, simulation accuracy, and functional integration. With the deepening of research on remote sensing modeling of complex surfaces, advancements in computer technology, and the application of multi-source remote sensing data, especially high spatio-temporal resolution data, 3D computer simulation models will play an increasingly important role in both theoretical research and practical applications of remote sensing.

Keywords:

Three-dimensional computer simulation model
Optical remote sensing
Ray tracing
Flux tracing
Radiosity

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1. Introduction

Remote sensing observations can capture Earth's surface reflections and radiation signals at multiple scales, wavelengths, angles, and time phases, making it a crucial tool for large-scale surface parameter inversion. Optical remote sensing (typically 0.4–50 μm) stands as a significant aspect of remote sensing modeling and inversion. Its observational data serves as a vital data source for global-scale monitoring of carbon, nitrogen, and water cycles, as well as radiation budgets. It plays a pivotal role in studies related to climate change, weather forecasting, vegetation monitoring, crop yield estimation, and drought early warning [1,2]. The accurate inversion of surface parameters (such as leaf area index, soil moisture content, temperature, and radiation components) from remote sensing signals is essential for realizing numerous remote sensing applications. Remote sensing models provide the theoretical foundation for understanding remote sensing signals and are vital tools for constructing linear or nonlinear functional relationships between these signals and ground parameters for remote sensing inversion [3].

Existing remote sensing models can be broadly classified into radiation transfer models, geometric-optical models, hybrid models, and three-dimensional (3D) computer simulation models [4,5]. Compared to radiation transfer, geometric-optical, and hybrid models in remote sensing physics, 3D computer simulation models offer accurate simulations of radiation transfer processes within three-dimensional scenes. Over the past few decades, modeling studies using 3D computer simulation models have made significant progress. Various models have been proposed, including DART (Discrete Anisotropic Radiative Transfer), RGM (Radiosity-Graphics combined Model), and FLIGHT (Forest Light Interaction Model). These models play crucial roles in forward modeling studies of complex surfaces, analyzing effects like mixed pixel and topographic variations on longwave and shortwave radiation budgets [6,7], and exploring relationships between vegetation indices such as NDVI, leaf area index (LAI), and photosynthetically active radiation fraction (FPAR) [8]. Additionally, with the introduction of inversion strategies like lookup tables, quasi-Newton iteration, and neural networks, coupled with improvements in computer performance, 3D computer simulation models are increasingly applied to remote sensing inversion studies, particularly in complex and diverse forest scenes [9]. Furthermore, advancements in remote sensing monitoring equipment and information technology have led to the emergence of near-ground remote sensing based on platforms like drones and land-based robots. These can acquire high spatio-temporal resolution monitoring data, providing invaluable support for more detailed vegetation parameter inversion using 3D computer simulation models [10].

In summary, 3D computer simulation models are a significant aspect of radiation transfer research, finding widespread applications in forward modeling of complex surfaces and remote sensing inversion. Over the past 40 years, these models have matured considerably. Disney *et al.* [11], Zhang *et al.* [12], Zhan *et al.* [13], and Chen *et al.* [14] have reviewed 3D computer simulation models from various perspectives. In recent decades, the application of high spatial resolution satellite and drone data, along with advancements in technologies like LIDAR (Active Light Detection and Ranging) and GPU (Graphics Processing Unit), has broadened the usage of 3D computer simulation models. **Figure 1** shows the literature searches related to "remote sensing" and "three-dimensional" in the Web of Science core database (as of June 28, 2019), indicating a rise in research on 3D structures/models, especially since 2013. To fully understand the differences among 3D computer simulation models and better apply them, this article reviews research progress and discusses current applications and future developments.

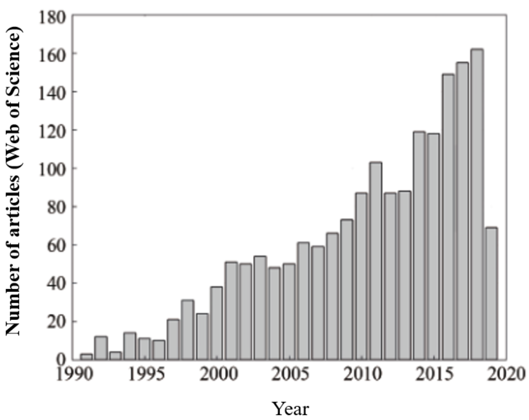


Figure 1. Number of papers related to "remote sensing" and "three-dimensional" in Web of Science

2. Basic principles and development history of the models

The foundation of optical remote sensing 3D computer simulation models lies in computer graphics. Computer graphics is a discipline that utilizes computers to represent, generate, process, and display graphics. Initially focusing on graphical research, the field has evolved to encompass the creation, storage, and manipulation of object models and images driven by technological advancements. The extensive scope of computer graphics research includes graphics hardware, standards, interaction techniques, raster graphics generation algorithms, curve and surface modeling, solid modeling, photorealistic graphics computation, and display algorithms, as well as scientific visualization, computer animation, natural scene simulation, virtual reality, and more [15].

In the field of remote sensing, computer simulation models have developed rapidly and are widely applied. Based on differences in research objects, studies on computer simulation models can be broadly categorized into those focusing on natural surfaces and those on urban buildings. Compared to urban buildings, research on three-dimensional computer modeling for natural surfaces is more mature. Therefore, using this as an example, the main principles of computer modeling, namely ray tracing and radiosity methods, are introduced. Additionally, a brief review is provided on the application of three-dimensional computer simulation models in studying remote sensing terrain issues.

2.1. Simulation models for natural surfaces

Figure 2 illustrates typical models and their extensions for natural surface simulation. In this article, apart from distinguishing between ray tracing and radiosity methods, ray tracing is further divided into flux tracing and Monte Carlo simulation methods. Details are provided in **Table 1**.

2.1.1. Ray tracing methods

One of the foundations of the flux tracing method is the discrete ordinate method, where the entire scene is divided into discrete voxels based on specific length, width, and height, such as the Flux Tracing mode in the

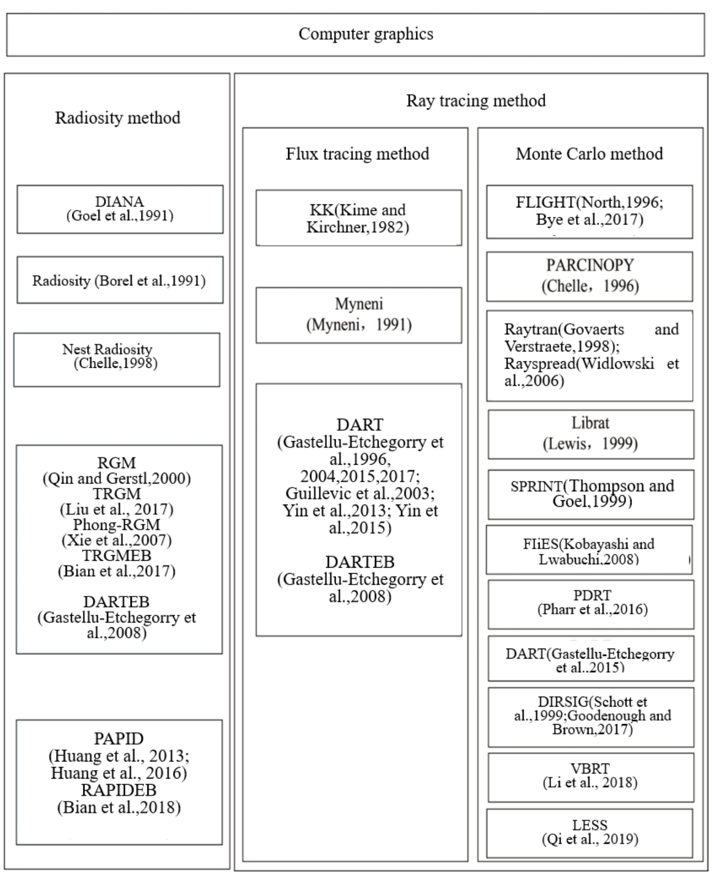


Figure 2. Typical three-dimensional models for natural canopies

Table 1. Typical three-dimensional computer model for natural canopies

Model	Literature	Theory	Scene	Basic unit	Band
FLIGHT	North, 1996 [16]	Ray tracing/Monte Carlo	Vegetation	Volume element	Visible light, Near-infrared, LIDAR
FLIES	Kobayashi and Iwabuchi, 2008 [17]	Ray tracing/Monte Carlo	Vegetation	Volume element	Visible light, near-infrared
Librat	Lewis, 1999 [18]	Ray tracing/Monte Carlo	Vegetation	Surface element	Visible light, near-infrared
PARCINOPY	España et al., 1999 [19]	Ray tracing/Monte Carlo	Vegetation	Surface element	Visible light, near-infrared
SPRINT	Thompson and Goel, 1999 [20]	Ray tracing	Vegetation	Surface element	Visible light, near-infrared
Raytran	Govaerts and Verstraete, 1998 [21]	Ray tracing/Monte Carlo	Vegetation	Volume element	Visible light, near-infrared
Rayspread	Widlowski et al., 2006 [22]	Ray tracing/Path tracing	Vegetation	Volume element	Visible light, near-infrared
PBRT	Pharr et al., 2016 [23]	Ray tracing/Monte Carlo	Vegetation, Architecture	Surface element	Visible light, near-infrared
DART	Gastellu-Etchegorry et al., 1996 [24]; Gastellu-Etchegorry et al., 2017 [25]; Gastellu-Etchegorry et al., 2004, 2015 [26,27]	Ray tracing/Flux tracing, Monte Carlo	Vegetation, Architecture, Mountain	Volume element, Surface element	Visible, near-infrared, thermal infrared, LIDAR
DIRSIG	Schott et al., 1999 [28]; Goodenough and Brown, 2017 [29]	Ray tracing/Monte Carlo, Path tracing	Vegetation, Architecture, Mountain	Volume element, Surface element	Visible, near-infrared, thermal infrared, LIDAR
VBRT	Li et al., 2018 [30]	Ray tracing/Path tracing	Vegetation	Volume element	Visible light, near-infrared
LESS	Qi et al., 2019 [31]	Ray tracing/Monte Carlo, Path tracing	Vegetation, Mountain	Volume element	Visible light, near-infrared
DIANA	Goel et al., 1991 [32]	Radiosity	Vegetation	Surface element	Visible light, near-infrared
RGM、TRGM Phong-RGM	Qin and Gerstl, 2000 [33]; Xie et al., 2007 [34]; Liu et al., 2007 [35]	Radiosity	Vegetation	Surface element	Visible light, near-infrared, thermal infrared
RAPID	Huang et al., 2013 [36]	Radiosity	Vegetation	Surface element	Visible light, near-infrared, thermal infrared

DART model. Kimes and Kirchner [37] introduced the KK model and provided a detailed explanation of the discrete ordinate method. Later, Myneni [38] conducted rigorous mathematical derivations for radiation interactions between voxels based on remote sensing radiation transmission principles, applying phase functions and hotspot functions during the calculation process. To account for multiple scattering within voxels and address the limitation of radiation transmission being based only on voxel centers, Gastellu-Etchegorry *et al.* [24] proposed the DART model. The radiation transmission process within voxels in the DART model can be briefly described by the following equation:

$$W_1\left(\Delta l_i,\boldsymbol{\Omega}_s \to \boldsymbol{\Omega}_v\right) = \int_{\Delta\Omega_v}\int_{\Delta l_i}\int_{2\pi} W\left(l,\boldsymbol{\Omega}_s\right)u_f \cdot \left|\boldsymbol{\Omega}_s\boldsymbol{\Omega}_v\right| \frac{g_f\left(j,\boldsymbol{\Omega}_f\right)}{2\pi} f\left(j,\boldsymbol{\Omega}_f,\boldsymbol{\Omega}_s \to \boldsymbol{\Omega}_v\right)\mathrm{d}\boldsymbol{\Omega}_f\mathrm{d}l\mathrm{d}\boldsymbol{\Omega}_v \qquad (1)$$

In the formula, Ω_S and Ω_V represent the solid angles of the light source and observation direction, respectively; Ω_f denotes the normal direction of the leaf; Δl_i is the radiation transmission distance within volume element i; $W(l,\Omega_S)$ represents the light source vector transmitted along the Ω_S direction for a distance l, where $l\in[0,\Delta l_i]$; U_f stands for leaf density; $g_f\,(j,\Omega_f)$ is the leaf angle distribution function for type j leaves; $f(j,\Omega_f,\Omega_S\rightarrow\Omega_V)$ represents the scattering phase function for type j leaves, which includes both Lambertian scattering and specular scattering. Multiple scattering between volume elements can be calculated iteratively based on single scattering. In the DART model, five scattering events can generally meet the accuracy requirements of most applications. The DART model has undergone several improvements. For example, Guillevic *et al.* [39] extended the DART model to the thermal infrared spectrum; Gastellu-Etchegorry *et* *al.* [26] expanded the applicable scenarios of the DART model, enabling radiation transmission process simulation in complex scenes including vegetation canopies, urban buildings, and terrain. Gastellu-Etchegorry *et al.* [27] released DART version 5, which added simulation of LIDAR data based on simulations in the visible, near-infrared, and thermal infrared bands for complex scenes. Recently, Gastellu-Etchegorry *et al.* [25] incorporated fluorescence simulation into the DART model. To improve the simulation accuracy of the DART model, Yin *et al.* [40] proposed a new discretization and sampling scheme called Iterative Uniform Squared Discretization (IUSD) for directional hemispherical space. Subsequently, to accurately simulate airborne and near-ground observations, Yin *et al.* [41] considered the field of view angle effect.

Monte Carlo simulation is generally considered the most accurate method in three-dimensional computer simulations [42]. It simulates canopy bidirectional reflectance factor (BRF) and surface albedo by tracking photon trajectories and considering photon numbers/energy. The Monte Carlo method can be further subdivided into forward ray tracing and Monte Carlo path tracing methods. The forward simulation process of radiation transmission based on photon energy can be represented by the following formula [31]:

$$P^{Q}(\lambda) = P^{0}(\lambda) \cdot \prod_{q-1}^{Q} \left(\frac{\pi f(q, \omega_i, \omega_o, \lambda)}{P_q} \right) \qquad (2)$$

In the formula, $P^Q(\lambda)$ and $P^0(\lambda)$ represent the initial energy of photon incidence and the energy after Q collisions in the c band, respectively. ω_i and ω_0 are the directions of incidence and emergence, respectively. $f(q,\omega_i,\omega_0,\omega_i)$ is the scattering phase function for the photon undergoing the qth collision in the ω_i band. P_q is the proportion of reflection and transmission during photon scattering. The order of multiple scattering simulated is determined by Q. The development of three-dimensional simulation based on the Monte Carlo principle is relatively mature. North [16] and Lewis [18] proposed the FLIGHT and Librat models based on the structural characteristics of forests and the Botanical Plant Modeling System (BPMS), respectively, utilizing the Monte Carlo principle. Subsequently, Kobayashi and Iwabuchi [17] extended the FLIGHT model by adding an atmospheric radiation transmission component, introducing the FLiES (Forest Light Environmental Simulator) model. Govaerts and Verstraete [21] presented the pure Monte Carlo model Raytran. Since it traces all photon paths emitted by the light source without introducing a weighting mechanism during photon collisions, it suffers from slow computation speed and low efficiency. Later, Widlowski *et al.* [22] proposed the Rayspread model based on the Raytran model. It introduces a secondary ray mechanism, which emits sub-rays toward the sensor while tracing the main ray to estimate the energy entering the sensor. This significantly improves the convergence speed of the simulation. The PBRT (physically based rendering) model proposed by Pharr *et al.* [23] has a wide range of applications in remote sensing and computer vision. Besides flux tracing simulation, the DART model also integrates a Monte Carlo forward simulation module [27]. To enhance the efficiency of Monte Carlo models in image simulation, a reverse tracing or Monte Carlo path tracing method is employed. The rendering process can be represented by Equation (3):

$$L_o(q,\omega_o) = L_e(q,\omega_o) + \cdots$$
$$+ f_{4\pi} f(q, \omega_i, \omega_o, \lambda) L_i(q, \omega_i) |\cos\theta_i| d\omega \qquad (3)$$

In the formula, $L_i(q,\omega_i)$, $L_e(q,\omega_0)$ and $L_0(q,\omega_0)$ represent the incident radiance, self-emitted radiance, and the radiance received by the sensor at collision point q respectively. Currently, three-dimensional computer simulation models that support path tracing include LESS (Large-scale remote sensing data and image simulation framework over heterogeneous 3D scenes) model, VBRT (Voxel-Based Radiative Transfer) model, and DIRSIG 5 (Digital Imaging and Remote Sensing Image Generation) model. The LESS model incorporates both forward and reverse Monte Carlo simulation modes, making it suitable for simulating large-scale scenes [31]. Beyond the modeling theory of Monte Carlo path tracing, the VBRT model also integrates an octree-based scene subdivision strategy to utilize LIDAR point cloud data for the construction of three-dimensional scenes [50]. To enhance the computational efficiency of the model, DIRSIG 5 adds path-tracing simulation strategies, SQT (spherical quad-tree) data structures, and GPU acceleration modules to the foundation of DIRSIG 4 [29].

2.1.2. Radiosity method

The radiosity method establishes the radiative interaction between surface elements in the entire scene through a series of radiative equilibrium equations:

$$B_i = E_i + x_i \sum_j F_{i,j} B_j \; i,j = 1,2,\cdots,2n_p \qquad (4)$$

In the formula, B_i represents the radiosity of a surface element, which is the total radiant flux density leaving the surface element. E_i denotes the radiation contribution from the sun, atmosphere, and the surface element itself. The term $x_i \sum_j F_{i,j} B_j$ accounts for the radiation contribution from all adjacent surface elements, where x_i represents the transmittance τ or reflectance p of the surface element, which can be determined based on the positional relationship between surface elements. The calculation of the visibility factor $F_{i,j}$ between surface elements and the solution of the radiosity equation are crucial processes in radiosity simulation. The former can be achieved through rasterization or ray tracing methods, while the latter can be implemented using iterative optimization techniques such as the Gauss-Seidel method. The ray tracing method can calculate sequential scattering terms for surface or volume elements, while the radiosity method only provides the final result of multiple scattering. Borel *et al.* [43] and Goel *et al.* [32] elaborated on the principles of radiosity, with Goel *et al.* [32] introducing the L-system to propose the DIANA model within the radiosity framework. Based on the DIANA model, Qin and Gerstl [33] optimized sensor observation modes, calculated the visible proportion of surface elements in the scene, and lighting/shadow ratios, presenting the RGM model. Subsequently, the RGM model underwent several improvements. For instance, Xie *et al.* [34] considered leaf specular reflection in the RGM model, while Liu *et al.* [35] added an emission term for surface elements in the RGM model, introducing Thermal RGM (TRGM). As the radiosity method requires constructing radiative equilibrium equations for each surface element, its solution efficiency significantly decreases with an increasing number of surface elements. Therefore, the radiosity method is often used for simulation studies of small-scale crop or forest scenes. To expand the application scope of the radiosity method, Chelle and Andrieu [44] combined the radiative transfer model (SAIL) with the radiosity method, proposing the nested radiosity model PARCINOPY. Huang *et al.* [36] improved the computational efficiency of the model by using a small number of large porous surface elements to replace a large number of small solid surface elements in the construction and solution process of large-scale forest scenes, known as the RAPID model. The RAPID model has undergone a series of optimizations, such as considering the effects of terrain undulations and the atmosphere, adding multiple observation modes, and supporting the simulation of LIDAR and microwave data [45].

2.1.3. Scene construction

The reconstruction of complex scenes is an important prerequisite for three-dimensional computer simulation models. The basic unit of radiosity models is triangular or polygonal surface elements, while the basic unit of ray tracing models can be surface elements or volume elements. Typical vegetation canopies include homogeneous canopies, row crops, forests, and mixed scenes. Generation systems for vegetation canopies are crucial methods for constructing vegetation scenes, such as L-systems, fractal theory, particle systems, and iterative function systems [46]. For homogeneous canopies, randomly distributed surface elements can be generated for reconstruction. The MELS (Modified Extended L-Systems) method [33] and the BPMS (Botanical Plant Modelling System) method [18] can be considered special L-systems that have been used to simulate the three-dimensional structure of crops like corn, cotton, and wheat. España *et al.* [19] proposed a three-dimensional structural model for corn based on a series of parametrization methods and simulated reflectivity using the Monte Carlo model PARCINOPY. Zhang *et al.* [47] simulated the three-dimensional structural characteristics of trees using Onyxtree software and conducted a simulation study using the radiosity model RGM. Additionally, OpenAlea and GroIMP are two of the most important platforms for simulating the three-dimensional structure of crops, capable of simulating the three-dimensional structure and light transmission processes of various crops such as wheat, corn, and rice.

Besides model simulation methods, LIDAR measurement techniques can acquire three-dimensional structural information corresponding to the studied surface. In recent years, LIDAR (Light Detection and Ranging) technology for 3D measurement has rapidly developed. Coupled with the widespread use of portable platforms such as drones, research and applications utilizing LIDAR sensors mounted on these platforms have become increasingly prevalent, providing valuable data sources for 3D modeling. For instance, Côté *et al.* [48] introduced a method for reconstructing the three-dimensional structure of trees based on LIDAR data and simulated canopy reflectance and directional transmittance using the Rayspread model in the reconstructed scenes. Schneider *et al.* [49] presented an application scheme for the DART model, which relies on both LIDAR data and ground measurement data, and compared the impact of modeling approaches based on tree crown structure and voxel assumptions on remote sensing imagery. Additionally, Liu *et al.* [10] developed a 3D canopy model for wheat based on LIDAR data and further proposed an inversion algorithm for wheat canopy leaf area index.

2.2. Simulation models for urban buildings

Three-dimensional computer simulation models are widely used in the study of urban building modeling. Here, we focus on the discussion of remote sensing optical modeling research, as summarized in **Table 2**. The 3D computer simulation of urban buildings can be broadly categorized into three types: simulation of simple building scenes, simulation of complex building scenes, and simulation of complex scenes including buildings and vegetation. In simple building scenes, buildings are often simplified as regularly distributed cubes. Based on a geometric optics-like modeling approach, Soux *et al.* [56] proposed the SUM model, which considers the sensor's field of view effect and can calculate the visible illumination/shadow ratio of each facet in the sensor's field of view. Kanda *et al.* [57] introduced the SM/HM model, which calculates longwave and shortwave radiation in the scene based on the geometric characteristics of building cubes and their mutual occlusion relationships. Fontanilles *et al.* [58] assumed buildings as "corridor" structures and proposed the TITAN model, primarily used to explain the contribution of various building components to remote sensing signals and simulate the directional thermal radiation characteristics of urban buildings. Zhan *et al.* [55] utilized the OpenGL-based computer model CoMSTIR for the study of urban thermal inertia. To reconstruct the 3D structure of complex urban buildings and model radiation transfer, Thomas *et al.* [54] proposed the AMARTIS model based on the ray-tracing method, which considers the influence of windows in buildings and the atmosphere. Krayenhoff and Voogt [51] presented the TUF-3D model, which combines ray-tracing and radiosity methods. These models primarily focus on simulating the building components in cities. However, vegetation parts such as parks and street trees also impact remote sensing observations in urban areas. Therefore, models like DART, ENVI-met proposed by Bruse and Fleer [50], and SOLENE introduced by Hénon [52] enable the simulation of remote sensing observation signals in complex scenes

Table 2. Typical three-dimensional computer models for building canopies

Model	Literature	Theory	Scene	Basic unit	Band
Envi-met	Bruse and Fleer, 1998 [50]	Finite difference	Buildings, Vegetation	Voxel	Visible light, Near-infrared, Thermal infrared
TUF-3D	Krayenhoff and Voogt, 2007 [51]	Ray tracing, radiosity	Buildings	Surface Elements	Visible light, Near-infrared, Thermal infrared
SOLENE	Hénon, 2008 [52]	Radiosity	Buildings, Vegetation	Surface Elements	Visible light, Near-infrared, Thermal infrared
AMARTIS	Miesch et al., 2004 [53] Thomas et al., 2011 [54]	Ray tracing/Monte Carlo	Buildings	Surface Elements	Visible light, Near-infrared
CoMSTIR	Zhan et al., 2012 [55]	Radiosity	Buildings	Surface Elements	Thermal infrared

including buildings and vegetation. Currently, 3D structure reconstruction technology for urban buildings is relatively mature. In 3D modeling research, besides existing datasets from municipal systems [59,60], the reconstruction of 3D structures of urban buildings can be achieved through observed videos and LIDAR data.

2.3. Simulation models for mountainous areas

Mountainous areas possess complex structures, and currently, there is relatively limited research on radiation transfer specific to these regions. Based on the Monte Carlo ray tracing model, Chen and Liou [61] simulated the three-dimensional surface thermal radiation transfer process. Later, Liou *et al.* [62] extended this Monte Carlo ray tracing model to mountainous scenes and used it to simulate the downward shortwave solar radiation and longwave thermal radiation in the Tibetan Plateau region. They compared the radiation differences between one-dimensional and three-dimensional surface assumptions. Gu *et al.* [6] proposed a parameterization scheme based on the Monte Carlo ray tracing model mentioned above and analyzed the influence of topography on the temporal and spatial variations of solar radiation using the Weather Research and Forecasting (WRF) model. Subsequently, Lee *et al.* [63] conducted a study on surface radiation budget in the Tibetan Plateau region using this model. To apply the RGM model to radiation transfer research in mountainous scenes, Zhang *et al.* [12] proposed a strategy of dividing large scenes into sub-scenes during the computation process, known as the LRGM model. Xie *et al.* [64] presented a strategy that combines the RGM model with the BRDF model. The DART model has also been extended and applied to mountainous scenes. For instance, Malbéteau *et al.* [65] introduced a normalization method based on the DART model to eliminate the influence of topography on surface temperature. Three-dimensional structural data for mountainous scenes can be obtained from global DEM products, such as the 30 m spatial resolution global ASTER GDEM v2 product produced by NASA and METI, the SRTM3 DEM product, and the GTOPO30 product from NASA.

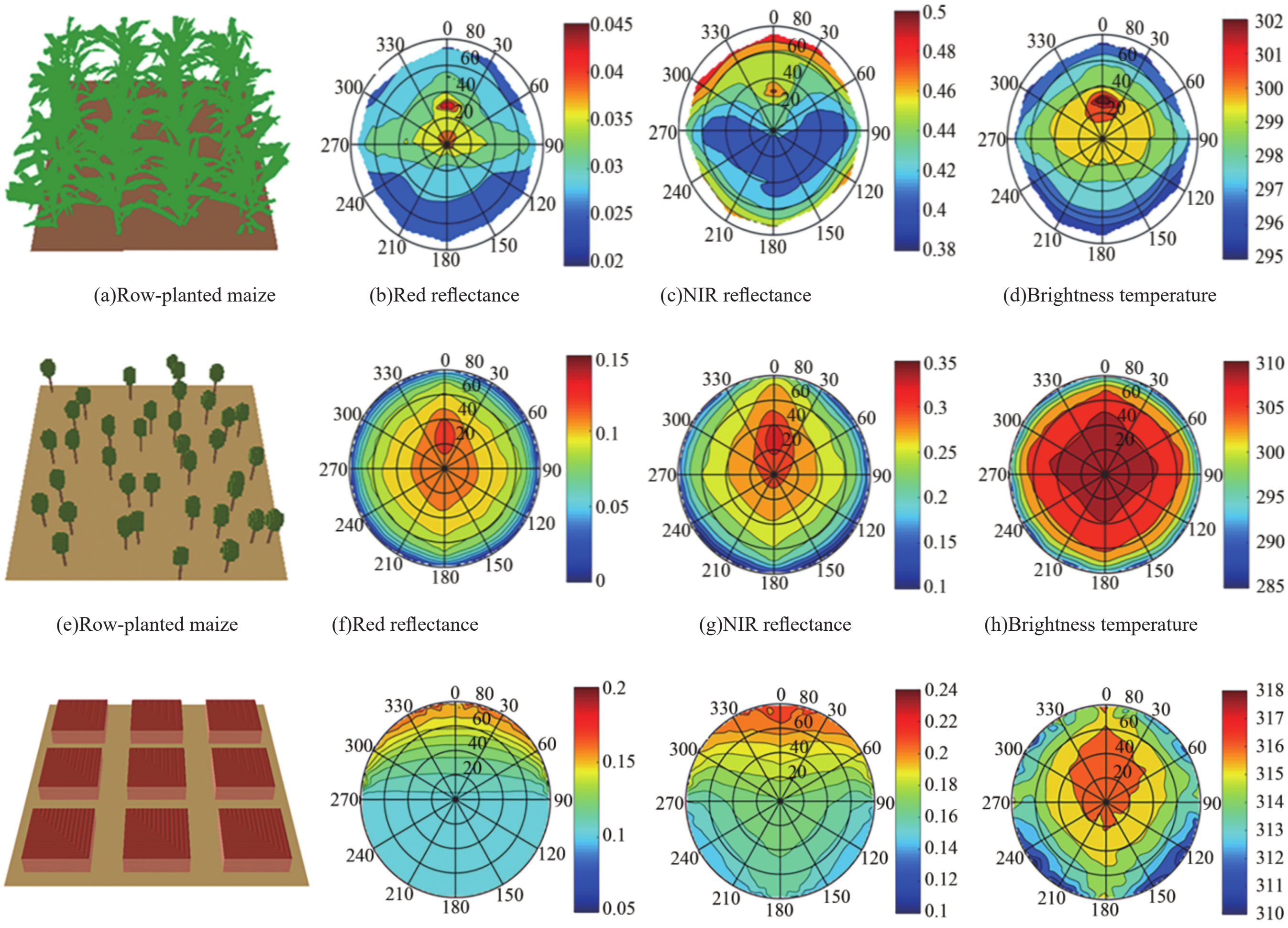
3. Applications of the models

With the development of high spatio-temporal resolution remote sensing technology, the application areas of three-dimensional computer simulation models are becoming increasingly widespread. **Figure 3** demonstrates polar plots of reflectivity/directional brightness temperature simulated using the TRGM and DART models for ridged cornfields, discrete forests, and simple building scenes in the red, near-infrared, and thermal infrared bands. Due to the influence of three-dimensional surface structures and differences in the physical properties of components, remote sensing signals vary with the study objects and observation angles. As three-dimensional computer simulation models can accurately simulate surface radiation transfer processes, they can be used to quantify the effects of mixed pixels and topographic relief in forward radiation transfer modeling and remote sensing inversion. When experimental data is limited or missing, three-dimensional computer simulation models can also be employed for sensitivity analysis and indirect validation of models or inversion algorithms. To summarize the application status of different models, **Figure 4** compares the number of citations and the number of related publications for various models in the Web of Science core database. The area corresponding to each model in **Figure 4** represents its proportional weight (as of September 10, 2019). The citation counts in Figures 4(a) and 4(c) correspond to the original literature where the models were first introduced, indicating the level of recognition for the models and theories. The number of model-related publications retrieved in Figures 4(b) and 4(d), i.e., publications mentioning the model names, reflects the subsequent development and application of the models. From Figure 4, it is evident that the DART model and the ENVI-MET model are widely used.

3.1. Modeling analysis of three-dimensional real structure scenes

Three-dimensional computer simulation models enable complex simulations of multi-band, multi-angle, multi-temporal, and multi-scale remote sensing observations of the Earth's surface. These models are instrumental in understanding the impact of three-dimensional surface scenes on remote sensing signals.

Computer simulation models are used to analyze relationships between vegetation indices (VI), leaf area index (LAI), and fraction of photosynthetically active

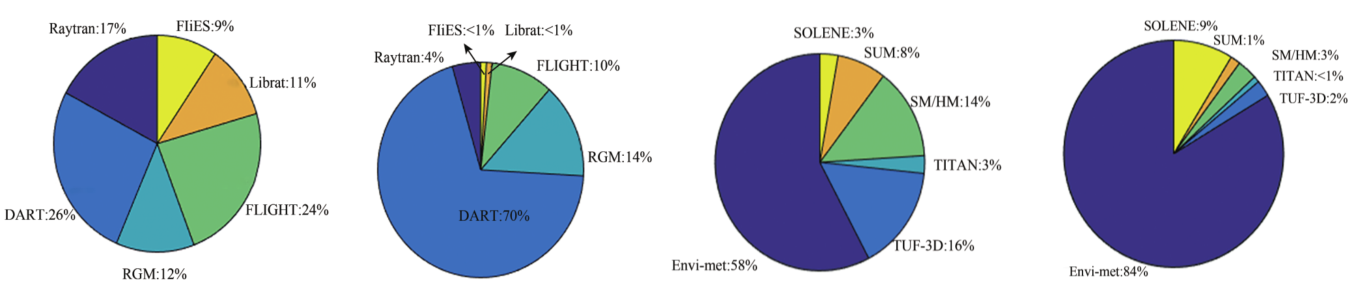


(a)Row-planted maize (b)Red reflectance (c)NIR reflectance (d)Brightness temperature

(e)Row-planted maize (f)Red reflectance (g)NIR reflectance (h)Brightness temperature

(i)Simple building (j)Red reflectance (k)NIR reflectance (l)Brightness temperature

Figure 3. Scenes and polar plots



(a)The number of citations of models corresponding to nature surfaces

(b)The number of model's corresponding papers

(c)The number of citation of models corresponding to urban surfaces

(d)The number of model's corresponding papers

Figure 4. Comparison of number of citations and papers for different models

radiation (FPAR). For instance, compared to the one-dimensional SAIL model, the RIRI-3D model provides simulation results that are closer to experimental observations from African savannas, making it suitable for analyzing the relationship between NDVI and FPAR [66]. Based on the DIANA model, Goel and Qin [8] analyzed the relationship between VI, LAI, and FPAR in three-dimensional real structure scenes of corn and poplar trees. Guillen-Climent *et al.* [67] utilized the FLIGHT model to estimate FIPAR and perform scale conversion analysis in furrow orchard scenes. Validation based on drone and ground measurement data demonstrated the high accuracy of simulation results from this computer simulation model.

These models are also applied to simulate visible and near-infrared bands of bidirectional reflectance factor (BRF), bidirectional reflectance distribution function (BRDF), and albedo in real structure scenes. Widlowski *et al.* [68] used the Raytran model to simulate BRF in the red and near-infrared bands for a three-dimensional forest scene, achieving more accurate results compared to one-dimensional models, with differences up to 40% in high-resolution images. The Rayspread and DART models are employed for simulating BRF in three-dimensional forest scenes and high-resolution remote sensing imagery, respectively. Compared to simpler models, three-dimensional computer simulation models offer a more precise analysis of the impact of canopy branches and trunks [68,69]. The DART model was utilized by Duthoit *et al.* [19] to simulate the BRDF of row-planted corn and analyze the influence of canopy clumping effects. In urban settings, the TUF-3D model aids in studying diurnal variations of effective albedo in buildings [51].

Furthermore, computer simulation models are used to simulate thermal infrared band emissivity and directional brightness temperature in three-dimensional scenes. Monte Carlo forward and inverse models simulate effective emissivity for non-isothermal and inhomogeneous pixels, providing valuable data support for emissivity definitions [61,71]. Three-dimensional computer simulation models have been employed to investigate the thermal radiation directional characteristics of various scenes. For example, the TRGM model, the ray tracing POY-RAY method, and the DART model have been used to simulate directional brightness temperature in row-planted corn, vineyard, and sparse forest scenes, respectively. Experimental data comparisons have shown that three-dimensional computer models yield accurate results and effectively capture the influence of structural features on thermal radiation directional characteristics in these scenes [72-74]. Given the pronounced heterogeneity of urban building scenes, three-dimensional computer simulation models find even broader applications. Specifically, TITAN, POV-Ray/SOLENE, and CoMSTIR have been utilized to simulate directional brightness temperature in buildings, emerging as essential tools for studying the thermal environment of urban structures [55,58-60].

3.2. Validation of forward models and inversion algorithms

Ground-based and airborne remote sensing experiments can provide validation data for forward simulation models and inversion algorithms. However, remote sensing experiments are costly in terms of manpower and resources, and the experimental data is limited, only corresponding to specific scenes and environmental elements. Especially in thermal infrared experiments, surface temperature varies continuously with solar angle and meteorological conditions. Three-dimensional computer simulation models can serve as important tools for indirect validation of algorithms and models.

Examples of indirect validation of parameterized models include: Qin and Goel [75] compared the performance of six parameterized hotspot models in homogeneous canopies based on the DIANA model. The results showed that the model that considered leaf size, shape, and orientation using a geometric-optical kernel performed best. Subsequently, Qin *et al.* [76] indirectly validated the performance of parameterized hotspot models in inhomogeneous crop and forest scenes using the DIANA model and proposed a method for parameterized models to consider mutual shading between components. Cao *et al.* [77] evaluated the performance of four parameterized thermal radiation directionality models in discrete forest scenes using the DART model as a benchmark.

Indirect validations of geometric-optical and hybrid models include: Kötz *et al.* [78] indirectly validated the simulation accuracy of the hybrid model GOESAIL in forest scenes using the three-dimensional FLIGHT model. Yin *et al.* [79] indirectly validated the simulation accuracy of the PLC model using the FLIGHT model. Pinheiro *et al.* [80] indirectly validated the simulation accuracy of the geometric-optical model MGP in the thermal infrared band using the DART model. Bian *et al.* [81] indirectly validated the simulation accuracy of the four-component UFR97 model, considering the vegetation clumping index, in row-planted crops and discrete forest scenes using the TRGM model.

Additionally, apart from indirect validation of models and algorithms, three-dimensional computer simulation models can also aid in the implementation of remote sensing experiments. For instance, model simulation results can serve as a reference for remote sensing experiments, providing theoretical support for selecting appropriate sampling times, frequencies, and locations for remote sensing experiments.

3.3. Remote sensing inversion of surface parameters

With the application of remote sensing inversion strategies such as lookup tables and neural networks, the use of three-dimensional computer simulation models as inversion tools for surface parameter inversion has become increasingly prevalent, particularly in complex and diverse forest scenes. Kimes *et al.* [82] conducted inversions of forest cover, LAI, and soil reflectance based on the DART model. The results indicated that compared to simple lookup table methods, the neural network approach provided stable, accurate inversion results with faster computation speeds. Combal *et al.* [9] performed inversions of forest LAI, chlorophyll content, and effective radiation based on the PARCINOPY model, comparing the advantages and disadvantages of lookup tables, quasi-Newton iteration, and neural network methods in solving ill-posed inversion problems using prior knowledge. Banskota *et al.* [83] proposed an inversion algorithm based on the DART model and discrete wavelet transform, utilizing visible and near-infrared hyperspectral data to invert forest LAI. Malenovský *et al.* [84] introduced an inversion algorithm based on the three-dimensional DART model and continuum removal, employing airborne high spatial resolution data to invert chlorophyll content in vegetation canopies. Ferreira *et al.* [85] presented an algorithm for inverting single-tree structure and chemical parameters based on the DART model and lookup tables, estimating narrow-band vegetation indices and the proportions of photosynthetic vegetation, non-photosynthetic vegetation, and shadows within pixels using hyperspectral data. Additionally, a global long-term remote sensing product for leaf area index was developed based on a three-dimensional radiative transfer model combined with MODIS imagery. The main algorithm of this product employs a lookup table generated by a stochastic radiative transfer model constructed from a three-dimensional radiative transfer model and a simplified version of it to invert LAI [86,87].

3.4. Application analysis tools

Three-dimensional computer simulation models can accurately simulate the relationship between component spectra or temperature and remote sensing observations at the canopy top, making them useful as analysis tools for various application problems such as fires, irrigation, and biomass. In African savannas, which feature a structural characteristic of upper tree canopies and lower grassland, Disney *et al.* [88] analyzed changes in surface reflectance before and after fires based on the Librat model. Three-dimensional computer simulation models can distinguish the radiative contributions of different surface components and can be employed for analyzing burned area estimation algorithms when observational data is missing. Sepulcre-Cantó *et al.* [89] proposed a method to distinguish between irrigation and rainfall based on surface temperature and NDVI, comprehensively analyzing this approach using the DART model. Malbéteau *et al.* [65] introduced a topographic correction method for surface temperature based on energy balance using the DART model. Comparisons with ASTER data demonstrated that the newly proposed method is more accurate than traditional multi-parameter linear regression techniques. Roberts *et al.* [90] analyzed the impact of canopy three-dimensional structure on combustible biomass inversion using the DART model.

4. Outlook for the model

Three-dimensional computer simulation models are crucial components of radiation transfer modeling. Over several decades of development, the focus of these models has gradually shifted from “how to model” to “how to better apply the models.” Although existing models have made significant progress, they still face challenges in practical applications. This section discusses the future development of these models from perspectives such as computational efficiency, simulation accuracy, and model integration.

4.1. Reducing computational time

Compared to one-dimensional and two-dimensional models, three-dimensional computer simulation models often suffer from slow computational speeds and long processing times, hindering their direct application in large-scale scene simulations and remote sensing inversions. Methods to improve model efficiency include hardware acceleration and algorithm optimization.

In recent years, with the advancement of computer graphics technology, high-efficiency image rendering software such as PBRT and LuxCoreRender has been gradually applied to remote sensing data simulation to enhance accuracy. Additionally, some three-dimensional computer simulation models have begun to incorporate the latest algorithms from the field of computer graphics. For instance, the DART model has integrated Embree, a ray-tracing library released by Intel, while the DIRSIG model has undergone reconstruction, incorporating path-tracing algorithms from computer graphics. Besides software improvements, advancements in computer hardware also support the rapid application of these models. Most existing models rely on CPU cores for computation. However, with the development of GPU technology, models based on GPU cores are expected to achieve significantly higher computational efficiency. Several models, such as LESS and VEBX, are planned to release GPU versions in the future.

Reducing computational time through hardware upgrades and developing new efficient simulation/rendering theories is the most direct approach. When studying homogeneous scenes or portions of scenes, the operational efficiency of the radiosity model can be improved by introducing high-precision analytical models or equivalent facets. For example, Chelle and Andrieu [44] and Xie *et al.* [64] enhanced efficiency by combining their models with SAIL and BRDF, respectively. Huang *et al.* [36] improved model efficiency by using porous large facets to represent numerous small solid facets, although this method risks reducing simulation accuracy. Monte Carlo ray-tracing models include forward and backward simulation modes, each with its own advantages and disadvantages. The forward mode is suitable for simulating energy balance-related issues, while the backward mode is more appropriate for simulating imagery and LiDAR data [30,31]. Therefore, models that incorporate both forward and backward modes possess stronger application capabilities and operational efficiency. Additionally, inversion strategies employing lookup tables, quasi-Newton iteration, and neural networks provide effective pathways for the application of three-dimensional computer simulation models in remote sensing inversion.

4.2. Improving simulation accuracy

In the fourth cross-validation of radiation transfer models conducted by Widlowski *et al.* [42], several typical three-dimensional computer simulation models were compared, revealing certain discrepancies even among Monte Carlo models. This underscores the necessity of continuing to enhance model accuracy.

Apart from optimizing the physical principles and radiation transfer mechanisms inherent in three-dimensional computer simulation models, simulation accuracy is also influenced by the level of detail in reconstructing the object of study and the spatial resolution of the sensor. Simplified scene-based computer simulations often fail to meet the demands of high-resolution remote sensing research. For instance, models like DART, TITAN, and SM/HM simplify building units. Conversely, three-dimensional modeling based on refined (more realistic) scenes is more beneficial for architectural design and high-resolution remote sensing applications. For example, the AMARTIS model considers the presence of highly reflective glass in buildings, resulting in more consistent simulation results with observations. Widlowski *et al.* [91] analyzed the impact of scene voxel size and sensor spatial resolution on Rayspread model simulation results, providing spatial resolution guidelines for different voxel sizes to achieve 95% simulation accuracy.

4.3. Enhancing model comparison and validation

Three-dimensional computer simulation models are often used as indirect validation tools for simpler models and algorithms. Therefore, the accuracy of these three-dimensional models themselves is a crucial consideration for such applications. Currently, validation of three-dimensional computer simulation models remains inadequate. Existing models are typically validated based on limited ground or airborne experimental data during their initial development. Dedicated validation efforts for these models are scarce. For instance, Sobrino *et al.* [92] evaluated the performance of the DART model on bare soil, grassland, and desert using airborne AHS, satellite ASTER data, and ground measurements. Additionally, due to inherent limitations in remote sensing experiments, such as spatial scale issues and temporal variations in heterogeneous scenes, cross-validation among computer simulation models has become a primary validation method. Apart from the comparative study conducted by Widlowski *et al.* [42], **Table 3** summarizes recent comparisons of model accuracy and computational time based on the same reference data. Currently, cross-validation efforts are primarily focused on the visible and near-infrared spectral bands, while cross-validation in the thermal infrared band remains limited.

Direct validation based on remote sensing experimental data is highly essential. Compared

Table 3. Evaluation results based on inter-comparison between models

Case	Model	Scene	Cross-validation between models	Runtime
1	RAPID vs RAMI (SPRINT3, RAYTRAN, RAYSPREAD)	Forest (ellipsoidal crown)	BRF: RMSE (red) = 0.002 RMSE (NIR) = 0.008	—
		Forest (conical crown)	BRF: RMSE (red, NIR) = 0.02	—
		Birch forest	BRF： RMSE (red, NIR) < 0.033	—
3	VBRT vs PBRT	Forest S3	Digital image: RMSE (red) = 0.5007 RMSE (NIR) = 4.2542 BRFs: RMSE (red) = 0.0032 RMSE (NIR) = 0.0373	—
	DART vs PBRT		Digital image: RMSE (red) = 2.4409 RMSE (NIR) = 9.0624 BRFs: RMSE (red) = 0.0046 RMSE (NIR) = 0.0578	—
4	LESS vs DART	Ellipsoidal crown	BRFs: RMSE (red) < 0.0002 RMSE (NIR) < 0.003	—
	LESS vs DART	Ellipsoidal/Cylindrical crown	BRFs: RMSE (NIR) < 0.001	—
	LESS vs DART (Facet) LESS vs DART (Turbid)	Forest canopy	Digital Image (0.2 m): R^2 (NIR, Facet) 0.92 R^2 (NIR, Turbid) 0.92 Digital Image (1.0 m): R^2 (NIR, Facet) 0.99 R^2 (NIR, Turbid) 0.97	Digital Image (0.2 m) DART (Triangle): 14.1 h; DART (Turbid): 3.0 h; LESS: 0.6 h
5	RAPID vs RGM	Homogeneous scene	—	View factor: RGM: 30 min, RAPID 1 min BRF (200 angles): RGM 8 min, RAPID 6 min
		Row structure scene	—	View factor: RGM: 2 min, RAPID 1 min BRF (200 angles): RGM 8 min, RAPID 7 min
		Checkerboard scene	—	View factor: RGM > 150 min, RAPID 3 min BRF (200 angles): RGM crashed, RAPID 13 min

to ground-based and manned aircraft experiments, unmanned aerial vehicle (UAV) remote sensing offers convenience, flexibility, and a larger experimental area, making it an increasingly important tool for remote sensing experiments. For instance, García-Santos *et al.* [93] utilized UAVs to obtain high-resolution ground temperature distributions. Therefore, UAV remote sensing data will serve as a crucial data source for validating three-dimensional computer simulation models.

4.4. Multi-functional integration

4.4.1. Multi-band integration

Multi-band joint simulation serves as a significant theoretical foundation for studying the application of multi-source remote sensing data. Incorporating more bands of information can enhance the accuracy of surface parameter inversion [94]. Three-dimensional computer simulation models play a vital role in multi-band joint simulation of complex surfaces. Several models like DART, RGM, and RAPID were initially developed for the visible and near-infrared bands and later expanded to other bands. Multi-band integration primarily involves two aspects in this context: (1) Expansion from visible and near-infrared bands to thermal infrared bands. For instance, to understand and define the effective emissivity of mixed pixels, Monte Carlo forward and backward simulation methods have been extended to the thermal infrared band. By considering the radiative emission term of components, models such as DART, RGM, and RAPID simulate the directional emissivity and brightness temperature of canopies. (2) Integrated simulation of optical and microwave bands. Although microwave remote sensing is not discussed in this article, the joint simulation of optical and microwave bands is currently an important research direction. For example, Disney *et al.* [95] constructed a three-dimensional scene to simultaneously simulate remote sensing observations in optical and microwave bands; Huang *et al.* [45] added microwave data simulation to the RAPID2 model; Zhang *et al.* [47] developed the 3-DMultiSim platform, which simulates remote sensing observations in visible, near-infrared, thermal infrared, and microwave bands. Apart from expanding the spectral range, modern three-dimensional computer simulation models have also enhanced their ability to simulate LIDAR observation data, such as the RAPID2, DART, and FLIGHT models.

4.4.2. Energy balance module integration

In the visible and near-infrared bands, canopy reflectance and albedo are primarily determined by the three-dimensional structure of the canopy, the spectral characteristics of its components, and the ratio of direct to diffuse radiation. However, in the thermal infrared band, apart from these factors, the directional brightness temperature of the canopy is also influenced by component temperatures, which constantly vary with solar and environmental radiation as well as meteorological conditions. By combining radiation transfer and energy balance modules, it becomes possible to simulate the temporal variation of surface temperature and thermal radiation directional characteristics. The integration of three-dimensional computer simulation models with energy balance is a crucial method for extending the temporal scale of complex surfaces, enabling a more comprehensive analysis of thermal radiation directional features and validation of other models. Gastellu-Etchegorry [96] augmented the DART model with an energy balance module similar to the corridor model, named DARTEB, expanding its capability for continuous time simulation in the thermal infrared band. Smith *et al.* [97] integrated an energy balance module into a radiosity model and subsequently calculated the illumination and shadow ratios of facets using a ray-tracing method, applying it to non-uniform row crop scenes. Huang *et al.* [98] inputted component temperatures simulated by the one-dimensional CUPID model into the TRGM model, analyzing the temporal variation of thermal radiation directionality in row crops. To fully leverage the advantages of three-dimensional computer simulation models, considering the impact of three-dimensional structure during component temperature simulation, Bian *et al.* [99] directly added a radiation transfer module to the TRGM model, introducing the TRGMEB model. Later, to simulate thermal radiation distribution in large-scale scenes, Bian *et al.* [100] combined the RAPID model with energy balance based on the same approach, presenting the RAPIDEB model.

The integration of three-dimensional computer simulation models with energy balance methods forms the foundation for studying urban heat island effects and the cooling impact of vegetation in urban built environments. Models like DARTEB and TUF-3D incorporate energy balance modules based on the corridor hypothesis, which considers mutual shading among three-dimensional structures during radiative transfer while assuming a corridor-like geometric configuration for buildings during calculations of sensible, latent, and surface heat fluxes. To more accurately simulate the energy budget processes in complex urban built environments, models like ENVI-met and SOLENE employ strategies from fluid dynamics software to calculate wind speed and water heat fluxes.

4.4.3. Integration of crop growth modules

Besides the diurnal variations in meteorological conditions mentioned above, seasonal changes in three-dimensional structures such as Leaf Area Index (LAI) and leaf angle distribution also occur due to vegetation growth. Existing three-dimensional simulations often target specific research scenarios and meteorological conditions, with pre-generated three-dimensional surface structures, thus can be considered as static scene simulations to some extent. The integration of crop growth models with radiative transfer models addresses the issue of changing three-dimensional structures of surface vegetation. Currently, this integrated approach has been applied in studies such as continuous time-series LAI inversion and crop yield estimation [101]. However, existing research primarily focuses on the integration of crop growth models with one-dimensional radiative transfer models like PROSAIL, neglecting the impact of three-dimensional vegetation structure changes. For instance, row-planted crops like corn and cotton undergo changes in leaf distribution from row structure to uniform as they grow. Therefore, developing integration schemes based on three-dimensional computer simulation models can enhance the accuracy of LAI and crop yield estimations.

4.4.4. Integration of vegetation functional modules

Beyond simulating radiative transfer processes, the use of three-dimensional computer simulation models for studying vegetation physiological functions is becoming more widespread. In addition to integrating with leaf-scale models like PROSPECT, LIBERTY, and FLUSPECT, models like TRGMEB and ENVI-met consider photosynthesis and respiration in leaves, making it possible to establish relationships between the physiological and ecological functions of vegetation and remote sensing observations. Duffour *et al.* [102] analyzed the relationship between maximum photosynthetic rate, evapotranspiration, and surface temperature. Simon *et al.* [103] simulated the patterns of vegetation transpiration rate and leaf temperature with changing solar radiation under different urban micrometeorological conditions using the ENVI-met model. Incorporating vegetation's physiological functional modules into three-dimensional computer simulation models lays an important foundation for their application in vegetation ecology research. The NOTG model, for instance, simulates not only radiative transfer processes but also synchronizes the simulation of carbon and nitrogen cycling between vegetation and soil, as well as forest growth [104].

4.5. Application expansion

Considering the aforementioned developments and trends, three-dimensional computer simulation models have significantly improved in terms of computational speed, simulation accuracy, and model coupling, meeting the requirements of most applications in terms of speed, accuracy, and functionality. Compared to existing research, the application scope of three-dimensional computer simulation models has also expanded. The following briefly introduces potential applications in remote sensing inversion, validation, and analysis.

To overcome the limitations of inversion using single remote sensing data sources, inversion strategies based on multi-source data fusion, including fusion and inversion of multi-scale, multi-band, multi-angle, and multi-temporal observation data, have rapidly developed [3]. Three-dimensional computer simulation models can simulate complex surface remote sensing observations at multiple scales, bands, angles, and times, making them valuable tools for multi-source remote sensing data fusion and inversion.

With improved computational speed and simulation accuracy, three-dimensional computer simulation models not only provide reference data to establish relationships between model inputs and remote sensing observations but also serve as tools for validating forward models and inversion algorithms. Additionally, these models can act as scale conversion tools, upscaling ground-based "point" measurements to "area" observations at the pixel level for validating satellite remote sensing products. Compared to existing empirical/semi-empirical scale conversion methods, validation methods based on three-dimensional computer simulation models have clear physical meanings and consider the impacts of three-dimensional surface structures and meteorological conditions, emerging as one of the important approaches for surface validation.

As analysis tools, three-dimensional computer simulation models often focus on the effects of three-dimensional surface structures on remote sensing observation signals (such as BRDF and DBT). With the coupling of different modules in these models, their simulation capabilities at diurnal and seasonal scales are expanded through integration with energy balance modules and crop growth models. Integration with vegetation functional modules further enhances the models' response mechanisms to meteorological changes. Therefore, three-dimensional computer simulation models can undertake more research in applications such as crop yield estimation, urban heat island analysis, fire warning, and drought monitoring in the future.

5. Conclusion

After nearly 40 years of development, three-dimensional computer simulation models have made significant progress and are widely used in indirect validation, analysis, and inversion in remote sensing. This article briefly introduced the development and applications of three-dimensional computer simulation models. Despite limitations such as slow running speed and high memory usage, these models are receiving increasing attention with the deepening of research on mixed pixels and mountainous areas. To meet application needs, three-dimensional computer simulation models have achieved a series of advancements in computational efficiency, simulation accuracy, and functional integration. This article discussed the progress, applications, and future trends of these models, hoping to contribute to addressing the question of "how to develop models to better meet application needs."

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