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Modeling carbon storage in urban vegetation: Progress, challenges, and opportunities

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ABSTRACT

Urban vegetation (UV) and its carbon storage capacity are critical for terrestrial carbon cycling and global sustainable development goals (SDGs). With complex spatial distribution, composition and ecological functions, UV is essential for global carbon cycling and climate change. Therefore, improving UV carbon storage capacity modeling is a research hotspot that deserves extensive investigation. However, the uniqueness of UV lead to great challenges in carbon storage modeling, including (1) limitations in data and algorithms due to complex and sensitive urban environments; (2) the severe scarcity of in-city field observation data (e.g., EC towers and field surveys); (3) difficulty in parameter inversion (e.g., canopy height, LAI, etc.); (4) poor transferability when migrating estimation models from natural vegetation to urban scenarios. The progress in carbon storage modeling in urban settings is reviewed, with detailed discussions on carbon storage modeling methods and major challenges. We then propose strategies to overcome existing challenges, including (1) implementing novel and improved remote sensing (RS) techniques (e.g., hyper-spectral, LiDAR, carbon satellites, etc.) to obtain enhanced structural and functional information on UV; (2) improving critical nodes of the earth observation sensor network, especially the distribution of EC towers in urban settings; (3) leveraging "Model-Data Fusion" technology by integrating big earth data with carbon estimation models to reduce the uncertainty in UV carbon storage estimations. This review provides new insights for modeling UV carbon storage and is expected to help the research community to achieve a better understanding of UV towards carbon neutrality.

1. Introduction

Urban vegetation (UV) is a small but essential part of the terrestrial ecosystems, having profound impacts on carbon balance locally and globally (Chen et al., 2020b; Walker et al., 2021; Zhuang et al., 2022a). UV mainly includes urban forests, lawns, gardens, street trees, etc. (Nowak et al., 2013). It is an essential reservoir in the carbon balance of urban ecosystems, which can directly or indirectly reduce the carbon content in the atmosphere (Zhang et al., 2022). The direct carbon sequestration of UV is carbon storage by vegetation growth. Indirect carbon sequestration is mainly through reducing the energy consumption of buildings, reducing the urban heat island effect, and guiding green transportation to reduce carbon emissions in the whole city (Lu et al., 2017; Sonti et al., 2022). UV releases a certain amount of carbon, such as the expansion of impervious surfaces, the death of vegetation, and lawn mowing (Pasher et al., 2014; Velasco and Chen, 2019). In

Abbreviations: UV, Urban vegetation; RS, Remote Sensing; SDGs, Sustainable development goals; SIF, Solar-induced chlorophyll; SOC, Soil organic carbon; AGB, Aboveground biomass; NPP, Net primary production; HANPP, human appropriation of net primary production; 3D, Three-dimensional; GEE, Google Earth Engine; ET, Evapotranspiration; EC, Eddy covariance; STM, Spectral-temporal metrics; ELM, Extreme Learning Machine; XGB, Extreme Gradient Boosting; MLP, Multilayer Perceptron; GEDI, Global Ecosystem Dynamics Investigation; NDVI, Normalized difference vegetation index; RVI, Ratio vegetation index; EVI, Enhanced vegetation index; GPP, Gross primary productivity; EOSN, Earth observation sensor network; CA, Cellular automata models; UHI, Urban heat islands; BIO-MASS, Biomass satellite.

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general, carbon reduction and compensation policies can be formulated to achieve the carbon balance target by combining the vegetation status of different city functional areas. In urban areas with severe carbon imbalances, carbon compensation from natural ecosystems (e.g., forests, grasslands) is explicitly sought. As the first "green line" to absorb greenhouse gases, research regarding UV carbon storage has become a hotspot (Buzzard et al., 2021; Kammen and Sunter, 2016). Cui et al. (2022) demonstrated a sustained increase in annual GPP from 2000 to 2016 in most global cities. Li et al. (2022) noted that future urban expansion will have a profound impact on global vegetation through habitat conversion, degradation, fragmentation, and species extinction. In 35 large Chinese cities, the total vegetation carbon storage was estimated at 18.7 million tons (Chen, 2015), while this number in Canada was 34 million tons (Pasher et al., 2014). Despite the less coverage of UV compared to natural vegetation (Williams et al., 2021), it has been identified as an essential regulator of the carbon cycle (Fig. 1) (Seto et al., 2012; Sharifi, 2021). Therefore, the carbon storage capacity of UV should not be ignored (Xu et al., 2018; Zhang and Shao, 2021).

Urban sustainability is linked to several goals in the SDGs framework, including SDG-11 and SDG-13 and SDG-15 (Li et al., 2021b; Simon et al., 2016). Continued urban expansion has led to many environmental challenges (Gong et al., 2020; Xu et al., 2018). Undoubtedly, it is particularly vital to estimate the carbon sequestration capacity of UV. Compared to natural vegetation, urban vegetation has two unique characteristics: (1) higher fragmentation of spatial distribution (Zhang and Shao, 2021); (2) more influenced by human activities, e.g., irrigation, fertilization, pest control, pruning, and waste disposal (Shi et al., 2016). The biochemical characteristics of urban vegetation are also specific. Studies have shown that UV waste (treatment of mowing material, apoplastic material, and dead plants) directly affects carbon sequestration capacity (Ji et al., 2011). Specifically, urban vegetation waste is collected and transported to landfills, where about 40 % of the carbon is sequestered over time. In contrast, the carbon in vegetation waste in natural ecosystems is generally released within three years or less (Thushari et al., 2020). In addition, it can be used as biomass fuel for power and heat generation, thereby reducing the consumption of fossil fuels (Thitanuwat et al., 2017). Due to the complexity of the "natural-society" attributes within cities (Venter et al., 2020), the simulation of UV carbon storage owns great uncertainty in terrestrial ecosystems, and its carbon sequestration capacity is likely to be greatly underestimated (Imhoff et al., 2004; Tang et al., 2021). If the terrestrial ecosystem carbon storage modeling is viewed as a wooden Liebig's barrel, the UV carbon storage modeling is its shortest stave. Therefore, it is paramount to understand what caused this shortcoming.

Remote sensing has greatly promoted the understanding of the spatiotemporal dynamics of the carbon sequestration capacity of UV (Liu et al., 2021c; Sonti et al., 2022). However, UV carbon storage modeling has been hampered by its unique challenges, including high spatial heterogeneity, shades cast by 3D urban structures, mixed pixels, and human disturbance, among others (Ardila et al., 2011; Timilsina et al., 2020). These issues lead to carbon storage simulation methods developed in natural vegetation failing to be translated to tackle issues in UV carbon storage. The development of multimodal RS techniques (e.g., multi-spectral, hyper-spectral, LiDAR, SIF, etc.) provides us with a great opportunity to handle the carbon sequestration capacity of UV (Thurner et al., 2014; Zhao et al., 2022a).

Accurate modeling of UV carbon storage remains to be a challenge. The main reasons include: (1) the limitations in data sources, vegetation extraction algorithms, and urban scene complexity (He et al., 2022); (2) in-city field observation data (including flux towers and field surveys) are insufficient to support large-scale carbon storage modeling (Nolan et al., 2021; Yu et al., 2021); (3) key parameters are difficult to invert in an accurate manner, e.g., canopy height, LAI, and others (Liu et al., 2021a; Zhao et al., 2022b); (4) estimation models with superior performance in natural vegetation have poor transferability to UV (Fang et al., 2020; Fatichi et al., 2014). Fortunately, some opportunities have been provided by advances in RS technologies to overcome these challenges, potentially improving the modeling of UV carbon storage at different scales (Fatoyinbo et al., 2021). Carbon satellites at more advanced spatiotemporal observation frequencies provide exciting new insights into vegetation physiology and potentially offer new avenues for UV carbon storage estimation. In addition, the rapid development of spaceborne LiDAR and hyper-spectral sensors renders crucial information for understanding the survival mechanism of UV by gauging vegetation structure and spectral characteristics (Coops et al., 2021; Zhao et al., 2018). Besides, the increasing popularity of supplementary observation instruments deployed on-site or on drones or other aircraft lead to an abundance of validation data, largely benefiting the design of

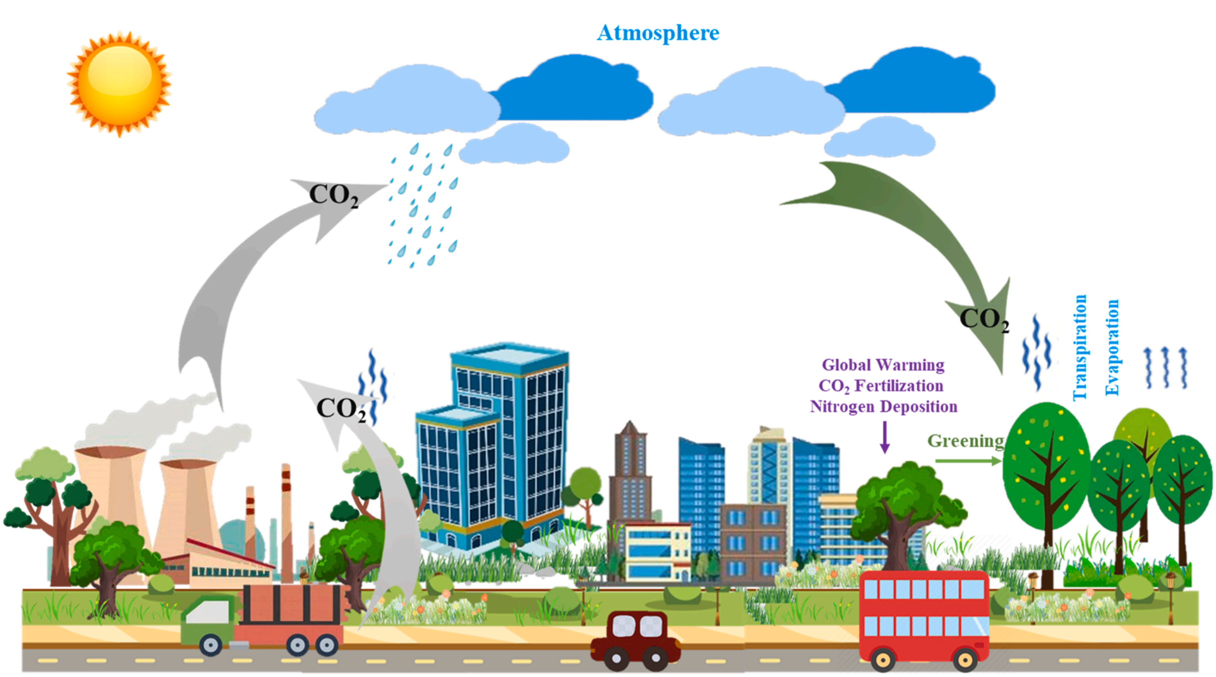

Fig. 1. Simulation diagram of carbon process in urban ecosystem.

robust UV carbon storage models.

In this article, we review the past achievements and current progress in UV carbon storage modeling (including data, methods, and models) and highlight the main challenges and limitations. We further outline future directions to overcome these major hurdles by embracing current and future RS (RS) data and techniques. Our discussion on UV carbon storage is from four perspectives: (1) the unique characteristics of UV that pose great challenges in carbon storage modeling; (2) key milestones in the methodological development of modeling carbon storage in UV; (3) issues that hinder accurate modeling of UV carbon storage; (4) the potential opportunities provided by the integration of “space-sky-ground” Big Earth data and model data fusion.

2. Key milestones in carbon storage modeling from natural vegetation to UV

In urban areas, human impacts on vegetation carbon storage can be divided into direct and indirect impacts. Direct impacts are caused by land use changes (e.g., impervious surface areas expansion, vegetation degradation, etc.) and human management (e.g., irrigation, fertilization, pruning, etc.). Indirect impacts are caused by changes in the growing environment of UV, which can be classified as positive and negative. Vegetation growth is promoted by increased light, heat island effect, atmospheric nitrogen deposition, and CO_2 fertilization effect in urban areas. On the other hand, waterlogging, air pollution, and soil heavy metals inhibit vegetation growth. Therefore, the human impacts on the UV carbon storage are much greater than the impacts on natural vegetation. Many efforts have been made to translate natural vegetation carbon modeling methods to UV. However, these methods fail to overcome the challenges of human impacts. The simulation methods of UV carbon storage can be divided into (1) sample plot inventory methods; (2) model simulation; (3) RS estimation; (4) integrative approaches driven by big earth data (Fig. 2).

2.1. Sample plot inventory

Determining the optimal sample size is critical for accurately estimating UV carbon storage and spatial distribution. The sample plot inventory method obtains the vegetation carbon storage of the urban ecosystem by multiplying the average carbon density in the urban plot and the corresponding area. Jia and Akiyama (2005) used the sample plot inventory method to estimate carbon storage in central Japan. Liao et al. (2009) coupled the sample plot inventory method with soil organic carbon (SOC) measurement to analyze the changes in soil taxa and surface SOC in Zhejiang Province, China. By conducting a methodologically consistent field campaign across the country, Tang et al. (2018) investigated carbon storage in various sectors of forests, shrubs, grasslands, and cropland in China. The samples obtained by the sample plot inventory method can serve as ground truth. Jo and Mcpherson (1995) used the sample plot inventory to quantify the annual carbon fluxes associated with green space storage and urban residential landscapes. Nowak et al. (2013) quantified the carbon storage by urban trees in the United States using the same method. The sample plot inventory continues the methodological system of field-forest surveys. It faces two major challenges: (1) demanding a lot of human and material resources; (2) lack of anisotropic growth regression equations for urban trees (Wen et al., 2010). The characteristics of high spatial fragmentation and strong heterogeneity of UV limit the applicability of this method to urban settings. In addition, plot selection is subjective and labor/time-consuming.

2.2. Model simulation

Some scholars developed carbon storage calculation models of urban vegetation based on ground survey data in the United States, e.g., CTCC (the center for urban forest research tree carbon calculator) and UFORE (urban forest effects model) (Havu et al., 2022). In addition, Citygreen, itree, and NTBC (national tree benefit calculator) are often used in UV carbon storage estimation. Citygreen estimates the carbon storage of urban forests based on GIS and RS data with the overall cover of vegetation. Citygreen typically uses vector data resulting in slower analysis, and the model is unsuitable for accurately assessing individual tree carbon storage (Du et al., 2016). The itree model allows carbon storage estimation at a single tree and urban forest scales (Jie et al., 2021). NFBC is suitable for estimating the carbon stock of specific tree species (Mchale et al., 2009). Using remote sensing technology to assess the carbon storage of UV has great advantages in terms of spatialization and continuous time series. This review focuses on the practical application value and future potential of remote sensing technology in carbon storage estimation of UV.

Aboveground biomass (AGB) plays an essential role in the process of modeling carbon storage of UV. Traditional methods obtain the AGB according to the algometric model corresponding to the specific tree species (Pappas et al., 2020; Velasco and Chen 2019). Despite the fact

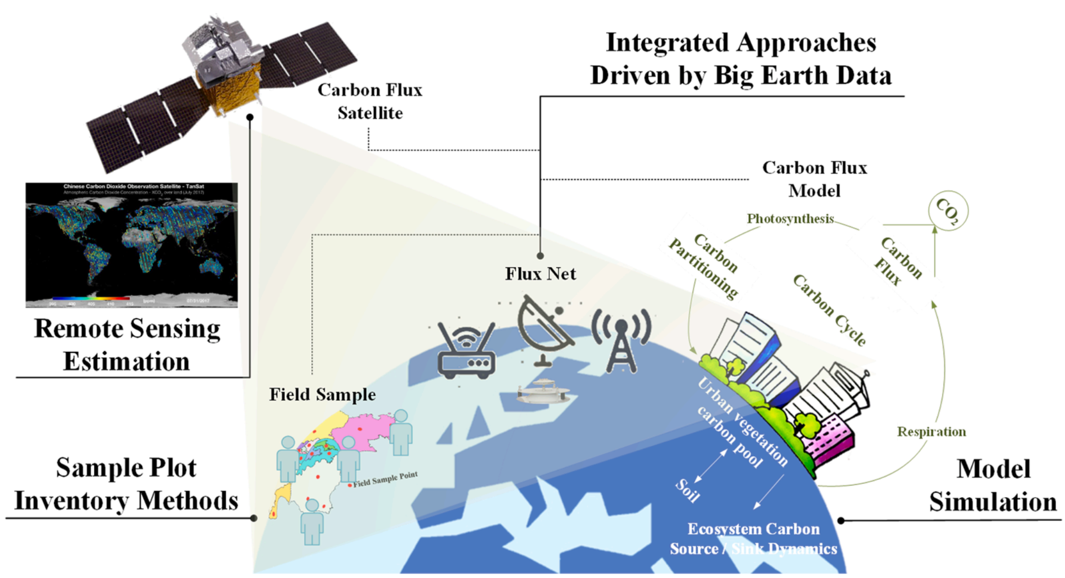

Fig. 2. The concept of four vegetation storage modeling methods.

that traditional methods can achieve carbon storage prediction at a local or regional scale, changes in spatial–temporal scales bring uncertainty to the simulation results, especially in complex urban environments. Another way to obtain vegetation carbon storage is by model simulation that considers vegetation's physiological and biochemical processes. The impact of urbanization on the carbon sink of land use is still debatable, despite the existence of many popular models. Habert et al. (2007) developed a method to quantify the human appropriation of net primary production (HANPP) in earth's terrestrial ecosystems. Subsequently, this method was widely used to study the interference of human activities on NPP from a planet to a pixel (Paudel et al., 2021). We believe HANPP is of very high practical value in the estimation of UV carbon storage.

In terms of the three-dimensional (3D) structure of vegetation, the ENVI-met software is used to simulate small-scale microclimates, as it captures the interaction among soil surface, vegetation, and air (Cilek and Cilek 2021; Simon et al., 2018). Another notable effort is the itree toolkit, which calculates and assesses the carbon storage of UV (Raum et al., 2019). These 3D structural models have the capability of accurately simulating the ecology and carbon sequestration process of UV, despite their limited access to the general public.

2.3. RS estimation

RS technology has promoted the understanding of the spatial pattern of UV carbon storage in many ways (Gong et al., 2022; Zhuang et al., 2022b). The free RS images with low resolution in urban built-up areas are generally insufficient to conduct high-resolution studies. However, the potential of remote sensing data for UV carbon storage estimation is gradually increasing with the availability of high-resolution satellite data (e.g., China's Gaofen series) and decreasing prices. Saatchi et al. (2011) used the sample plot inventory method, optical satellite images, and LiDAR data to estimate carbon storage. Wolf et al. (2016) combined satellite RS and atmospheric inversion modeling to design an extensive ecosystem flux network to quantify droughts' effects on biosphere-atmospheric carbon. Tong et al. (2020) estimated the growing carbon storage in southern China using multispectral and microwave RS data. Li et al. (2020) constructed a model for estimating urban vegetation biomass using field observations and Sentinel-2A image data. Zhang and Shao (2021) estimated urban aboveground biomass using LiDAR and high-resolution remote sensing images, Hengqin, Guangdong Province, China. RS-based estimation of UV carbon storage has numerous advantages, thanks to the large spatial overage, regular temporal continuity, and low cost. However, challenges, e.g., quantification uncertainty, modeling integration, algorithm transferability (Schimel et al., 2019). It is difficult to estimate the carbon storage of UV roots using remote sensing techniques. Regarding the carbon storage of vegetation roots, accurate measurements can be made at small scales using chemometric methods. At large spatial scales and without destroying the vegetation, we suggest a constant conversion based on the egetation types and the above-ground carbon storage.

2.4. Modelling UV carbon storage in the era of Big Earth Data

Big Earth Data has many memorable features, e.g., massive, multisource, heterogeneous, multi-temporal, multi-scale, and non-stationary, with strong spatiotemporal and physical correlations and the controllability of data generation methods and sources (Guo 2017; Guo et al., 2016). How to dynamically couple observations with different mechanisms is a critical technical challenge for monitoring UV in the Big Data era. Chen et al. (2020) developed a new monitoring model with an observation system-level coupling model, daily loose coupling and emergency tight coupling. This monitoring model achieves dynamic aggregation of observations, processing algorithms, and application models through an information model and an open interface bus that shields the observation system from interface and processing algorithm differences. The advance in Big Earth Data has mitigated the problem of insufficient data sources for carbon storage estimation in UV (Campbell, 2021; Xia et al., 2020). The fusion (or joint use) of multivariate cross-modal data has been proven promising to accurately characterize the carbon storage capacity of vegetation by overcoming the data insufficiency if a single data source is relied upon (Liu et al., 2021b; Zacharias, 2021).

However, petabyte-level Big Earth Data poses new challenges and demands new data download, storage, and manipulation paradigms. The emergence of cloud computing platforms provides unprecedented opportunities for data processing and analysis in Earth Sciences, with carbon storage monitoring in urban settings being one of the beneficiaries (Buzzard et al., 2021). Google Earth Engine (GEE) is a typical representative. For example, Zhang et al., (2019) estimated global evapotranspiration (ET) and GPP datasets using a coupled diagnostic biophysical model on the GEE platform. MODIS data products (LAI/albedo and reflectance), GLDAS climate stress data, and 95 EC flux towers were also involved in this process. The advances in cloud computing greatly facilitated studies that demand massive data input and fusion.

2.5. Historical summary

As an underexploited component of terrestrial ecosystems, UV carbon storage has received more attention. In particular, the advances in RS science and technology have provided new options for us to estimate urban carbon storage. Despite the existing efforts, the carbon storage medeling of UV remains to be a challenge and deserves further investigation.

3. Key challenges in modeling carbon storage of UV by using remote sensing technologies

Remote sensing technology has been proven to be beneficial in terms of assessing the carbon storage of UV. In recent decades, global vegetation carbon storage investigations have made fruitful progress. Despite these successes, challenges remain in the structure, function and carbon sequestration capacity of UV. We summarized the key challenges in UV carbon storage modeling as follows. (1) The complex urban scenes (e.g., building occlusion and shadow occlusion) and the limitations of RS images (e.g., spatial–temporal resolution and spectral characteristics) create hurdles in the large-scale extraction of UV. (2) The high heterogeneity of UV types (e.g., forest, flower beds, lawns, and fences) and the high fragmentation of spatial distribution lead to the difficulty in key parameter inversion. (3) The distribution of field observation data and eddy covariance (EC) towers are relatively sparse in urban settings, posing challenges in the validation process. (4) Models (or algorithms) designed based on natural vegetation fail to perform in a satisfactory manner when they are migrated to urban settings.

3.1. Spatiotemporal information extraction of UV: fragmentation, heterogeneity, and shadows

As the first step of the modeling process, information regarding UV density is essential in carbon storage modeling. Photogrammetry and RS technology provide rich data that benefit UV information extraction given the spectral, spatial, temporal, horizontal, and vertical characteristics (Huang et al., 2021c). UV has complex spatial structures, with some having similar spectral properties (Abdollahi and Pradhan, 2021). The distribution of UV is fragmented and heterogeneous, influenced by human activities and urban planning (Nesbitt et al., 2019). The heterogeneity of its horizontal structure can be investigated with additional data sources. The effective fusion of multiple sources provides new opportunities for improving classification models and evaluating algorithm performances (Pu and Landry, 2012). In the built-up area, the spatial distribution of vegetation is more fragmented; however, the increasing availability of high-resolution remote sensing images allows us to gauge vegetation dynamics at fine spatiotemporal granularity (He et al., 2022).

The improvement in spatial–temporal resolution of RS images unavoidably leads to the emergence of salt-and-pepper noises in pixel-wise classification. Advanced methods, e.g., object-oriented, STM, ELM, XGB, MLP, and AdaBoost (Schug et al., 2020), have been applied to extract UV information. It is important to understand the scope and generalizability of these methods (Gasparovic and Dobrinic, 2020). In addition, balancing accuracy and efficiency deserves consideration (Wei et al., 2021) demands scholars to determine the optimal variable set when using multisource RS data so that the data dimension and computational complexity can be reduced (Yu et al., 2020). Hyper-spectral imaging can detect continuous spectral features of ground objects, thus improving the identification and classification of ground objects (Zhong et al., 2021). Studies have shown that the effective fusion of hyper-spectral and multi-spectral can provide more detailed information on urban land uses (Weng et al., 2008; Zhang et al., 2018), allowing for a better understanding of UV (Awad 2018; Pan et al., 2013).

Besides the horizontal structure, UV is also heterogeneous in its vertical structure. Efforts have been made to involve characteristics of vegetation canopy (e.g., physiological features) in calculating biomass and carbon storage (Zhang and Shao, 2021). In addition, stereoscopic mapping satellites can obtain three-dimensional surface data on a large scale. However, it is challenging to combine multisource optical images to extract UV information (Liu et al., 2019). Meanwhile, in the extraction of long-term UV information, phenological parameters of vegetation are valuable attributes that can further improve the extraction accuracy (Cadenasso et al., 2007). Qiu et al. 2020 encouraged more suitable classification systems to address the classification between confusing vegetation types and land feature types easily confused with vegetation.

3.2. Inversion of key parameters: VIs, LAI, canopy height, and biomass

Many parameters (e.g., spectral VIs, LAI, and canopy height) are essential in the simulation of UV carbon storage. In recent decades, spectral VIs have been developed and applied (Gao et al., 2020; Huang et al., 2021b; Xue and Su, 2017). As an important indicator of canopy structure, LAI has been widely used in various biophysical and biochemical models (Huang et al., 2021a; Sun et al., 2022), serving as a crucial input for urban carbon modeling. Multi-spectral, hyper-spectral, and airborne LiDAR data were used to estimate LAI with great success (Lee et al., 2021; Sadeh et al., 2021). The rapid development of spaceborne LiDAR and spaceborne hyper-spectral data in recent years has made large-scale LAI estimation possible (Li et al., 2022; Zhang et al., 2021a). However, how to fuse information from active and passive multisource sensors, e.g., multi-spectral /hyper-spectral and airborne/spaceborne LiDAR, remains to be a challenge.

Accurate canopy height can reduce the uncertainty of carbon storage models (Kamoske et al., 2021; Malambo and Popescu, 2021). The performance of multisource and cross-modal RS data in canopy height estimation varies widely. Optical RS signals usually fail to obtain accurate vertical information on vegetation canopy (Ma et al., 2019). Thanks to its capability in canopy penetration, microwave RS can obtain vegetation's vertical structure, however, with strong influences by terrains (Bruening et al., 2021). LiDAR has been widely used in vegetation height inversion (Liu et al., 2021a). Spaceborne LiDAR, with its unique advantages in coverage, makes national/global-scale canopy height studies possible (Queinnec et al., 2021). GEDI, ICESat-2, and NISAR have potentially complementary advantages in different regions and applicable scenarios. How to develop and test fusion methods of multisensory data to obtain accurate UV heights deserves further exploration (Campbell et al., 2021; Musthafa and Singh, 2022). Apart from multispectral and LiDAR, synthetic aperture radar (SAR) data is well utilized in biomass estimation and carbon storage (Bergen et al., 1998; Fatoyinbo et al., 2021; Mandal et al., 2021) due to the penetration of long-wave SAR into the vegetation canopy (Pourshamsi et al., 2021). Compared with optical remote sensing data, SAR data can break through the high biomass saturation problem in optical models (Cartus and Santoro, 2019). The biomass mission by European Space Agency (ESA) plans to launch a P-band SAR in 2023 to provide global ground biomass data, which can significantly improve the saturation point of forest biomass inversion by combining L- and P-band (Soja et al., 2021). In addition, other parameters (e.g., FAPRA, and vegetation indices) can be limited by data sources and methods during the inversion process (Zhang et al., 2021b).

3.3. Constraints in observational data and simulation models

Compared with natural landscapes, ground-based observational data in urban settings are more sparse (Schimel et al., 2019; Smith et al., 2020a), presumably due to the lack of UV census work, the sparseness of flux networks, and urban data sensitivity (Zipkin et al. 2021). Mainstream flux networks (including FLUXNET, AmeriFLUX, ILTER, and ChinaFLUX, etc.) (Baldocchi et al., 2018; Houghton 2020) suggest that flux towers are distributed widely in East Asia, North America and Australia, while sparsely in Africa, South America, Middle East, and Central Asia (Baldocchi et al., 2018). In particular, flux towers in urban environments are rare and with limited accessibility (Vaidya et al., 2021; Yuan et al., 2013). The unevenness, sparseness, and limited accessibility of observational data greatly restrain the modeling of UV carbon storage (Wu et al., 2021). Thus, we call for the expansion of flux networks into urban settings for better carbon storage modeling.

Vegetation growth is an important input in ecological process model simulation (Fer et al., 2021; Xu and Trugman, 2021). As ground objects and vegetation are complex in urban environments, it is difficult to directly transfer models that target natural vegetation to urban settings (Hemes et al., 2021). UV is characterized by its low density, which reduces potential competition with surrounding trees for light and other resources (Davies et al., 2011). The latest available sensors (e.g., multispectral and LiDAR) produce high spatiotemporal information that largely improves the assessment of individual urban trees.

4. Recommendations and future directions

The above challenges and limitations point to the insufficient understanding of physiology and carbon sequestration capacity within urban areas. This gap leads to uncertainty in carbon modeling across terrestrial ecosystems and inhibits sustainable urban development (Vaglio Laurin et al., 2020; Zhang et al., 2021c). We believe the estimation of urban carbon storage can be improved from the perspectives of data, methods, and models. The applications of new RS techniques to modeling carbon storage should receive wide attention. In this session, we document and discuss the opportunities in urban carbon modeling.

4.1. Moving beyond "vegetation index"

The traditional spectral vegetation index only reflects the "potential photosynthesis" of vegetation through "greenness"(Gao et al., 2020). Due to the patchy distribution of UV, the assessment ofcarbon storage can be seriously affected by mixed pixels, resulting in great uncertainty. Moreover, the unique characteristics of UV lead to its unique carbon sequestration process that is different from that of natural vegetation. Thus, we encourage new vegetation indexes and methods to be developed for estimating carbon sequestration (Fig. 3).

Despite that CO_2 ground monitoring stations (networks) greatly support the calculation of terrestrial vegetation carbon fluxes, our understanding of the spatial–temporal characteristics and mechanisms of carbon storage needs to be improved (Monteil et al., 2020; Pastorello et al., 2020). The XCO2 data retrieved from satellites (e.g., GOSAT and OCO-2) allow the quantification of spatial–temporal dynamics of vegetation carbon storage (He et al., 2017; Wang et al., 2020). However,

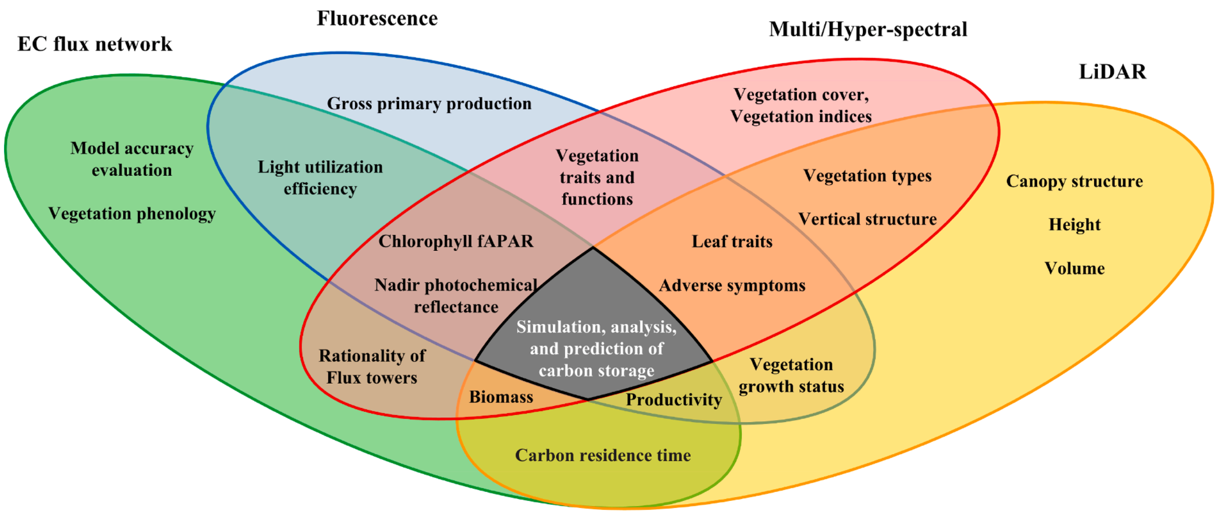

Fig. 3. Potential synergies of multisource observational data in improving the understanding of the biophysical structure and carbon sequestration capacity of UV. Observations from each data source (colored ellipses) and vegetation function parameters (black text) can be achieved (Stavros et al., 2017).

obtaining satisfactory accuracy with satellite RS alone is challenging for UV carbon storage modeling. Thus, the coordination between ground-based monitoring and aerial RS is essential to achieving accurate UV carbon storage (Filges et al., 2015). At present, increasing efforts on global carbon satellite monitoring have been made by many countries and organizations. With the key technological breakthroughs of carbon satellites, high-precision carbon scientific sharing products can be achieved. These new carbon satellites pave the way for accurate simulation of UV carbon storage.

In addition, hyper-spectral RS has a unique advantage in monitoring vegetation growth (such as LAI and fPAR) (Heiskanen et al., 2013; Liang et al., 2015) and physiological and biochemical status (e.g., chlorophyll, nitrogen, etc.) (Castaldi et al., 2016; Liang et al., 2016). The new index constructed from hyper-spectral images well-reflects the changes in leaf and canopy light use efficiency in shrub ecosystems (Stagakis et al., 2014). The advantages of hyper-spectral RS demand further exploration when addressing the carbon storage challenges in urban environments (Mariotto et al., 2013; Zhang et al., 2016).

4.2. Taking advantage of the Earth observation sensor network (EOSN)

The Earth observation sensor network (EOSN) embodies the concept of the smart planet, with comprehensive event perception capabilities, powerful collaborative observation capabilities, efficient data processing capabilities, and intelligent decision support capabilities (Fig. 4) (Chen et al., 2020a; Le et al., 2021). From the perspective of systems science, EOSN integrates various sensor resources with each sensor node having independent event sensing and observation capabilities (Shao et al., 2021), forming a self-organizing dynamic and collaborative observation system suitable for fine-grained urban monitoring (Fu et al.,

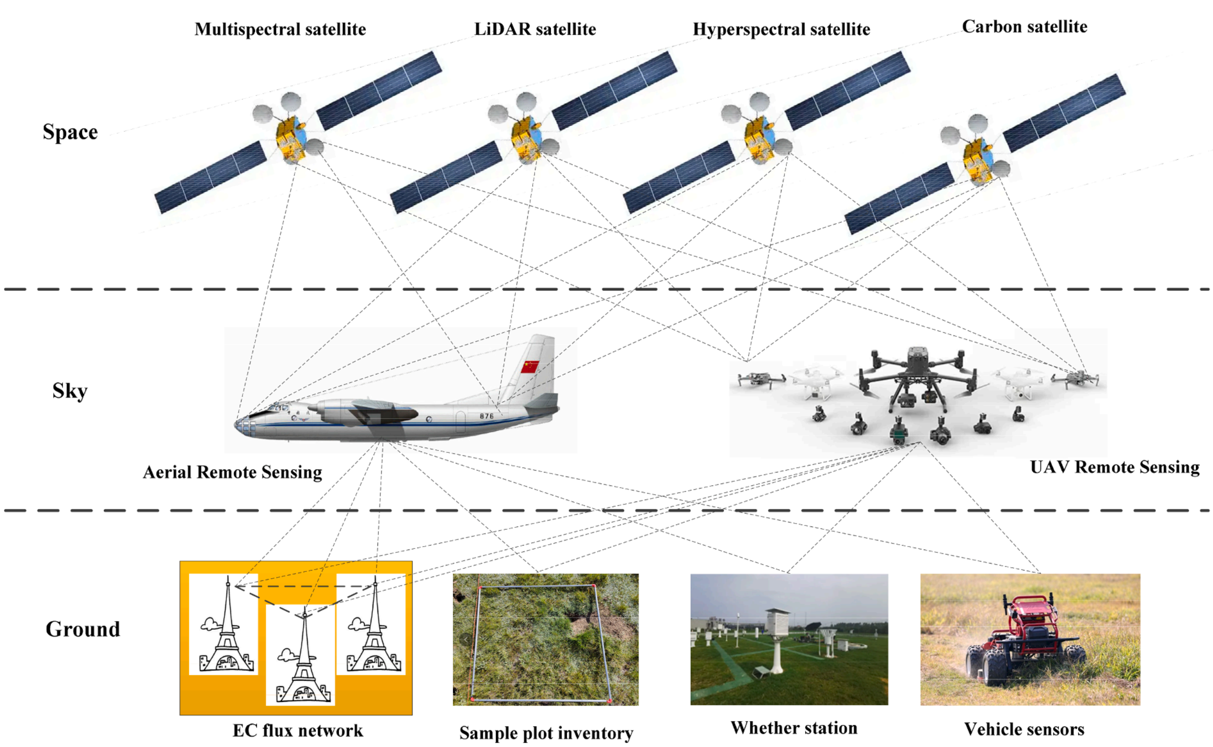

Fig. 4. “Space-Sky-Ground” integrated cyber-physical earth observation sensor network.

2021). For a specific observation target, the bottleneck problem of sensors, data and information failing to be complemented via current observation platforms can be solved by systematically integrating all nodes. In addition to RS images of various modalities, we detail the important node "eddy covariance (EC) flux towers", whose expansions are particularly useful for modeling UV carbon stocks.

EC flux towers enable direct observation of net exchanges or fluxes between ecosystems and the atmosphere (Baldocchi, 2014; Baldocchi, 2003). EC flux towers own three specific advantages. (1) Sensors on the EC flux tower make continuous observations that capture land–atmosphere exchanges at various temporal scales (Chu et al., 2021). (2) Compared to other methods, artifacts from other activities are not introduced during EC measurements. (3) EC captures a myriad of biotic and abiotic processes, which aggregate fast and slow, overt and hidden, above and below ground carbon pathways (Knox et al., 2019). Sensors mounted on flux towers correlate carbon sequestration capacity and UV spectral index through repeated measurements. However, the highly sparse distribution of EC flux towers in urban settings usually fails to support the fine-grained carbon modeling of UV (Gong et al., 2019). We believe the reasonable arrangement of urban EC flux towers have great potential in solving challenges in urban carbon storage simulations.

4.3. "Model-Data Fusion" aids carbon storage simulation of UV

The uniqueness of UV leads to great difficulty when existing models that target natural vegetation are migrated to urban settings. Existing studies suggested that "Model-Data Fusion" is beneficial for terrestrial carbon cycle estimation (Raczka et al., 2021). The essence of "Model-Data Fusion" is to fuse multiple observations under the carbon cycle framework. Considering the data and model errors, a higher-precision, spatiotemporally consistent carbon cycle estimation can be achieved by establishing an optimal fusion mechanism that integrates model information and observational information (Li et al., 2021a; Niu et al., 2020). "Model-Data Fusion" includes two aspects, i.e., 1) data assimilation and 2) model parameter estimation (focusing on the optimal design of time-invariant or partially time-varying parameters) (Geer, 2021). We present a conceptual overview of how multisource Big Earth Data could be incorporated with "Model-Data" methods to reduce the simulation uncertainty in UV carbon storage (Fig. 5). Firstly, the POI data will help determine the distribution and properties of vegetation in the urban areas, as well as the duration, type, and intensity of surrounding human activities. Secondly, the priori knowledge provided by the geological knowledge mapping (GKM) is used to simulate vegetation carbon storage in urban areas. To address the problem of human activities that are difficult to identify and distinguish by multiple data sources, this study perform classification and clustering by deep reinforcement learning featuring the semantic spatio-temporal association of human activities in GKM. Finally, the quantitative effects of human activities on urban vegetation carbon storage can be explored in the future by establishing a detailed and complete database of urban vegetation carbon storage life cycles.

Specifically, the combination of data assimilation and cellular automata models (CA) has demonstrated superior performance and is widely used to predict urban sprawl (Zhang et al., 2013) and urban heat islands (UHI) (Huang et al., 2017). Therefore, we encourage more advanced "Model-Data Fusion" methods to be developed in urban environments, aiming to adapt to the unique vegetation characteristics and high human impacts (Smith et al., 2020b). In addition, the biomass satellite (BIO-MASS), with a scheduled launch in 2022, is expected to bring new opportunities to UV carbon storage modeling.

5. Conclusion

Urban vegetation (UV) is critical for terrestrial carbon cycling and SDGs. In light of the complex urban conditions, the carbon storage simulation of UV tends to present great uncertainty. This review summarizes existing efforts and provides new directions for urban carbon storage simulations. We observe that the modeling of UV carbon storage faces many unique challenges. The emerging observational techniques, models (or methods), and concepts are expected to provide new opportunities for a deeper understanding of UV carbon storage. We identify the following potential directions: 1) implementing novel and improved RS techniques (e.g., SIF, hyper-spectral, LiDAR, carbon satellites, etc.) to obtain enhanced structural and functional information on

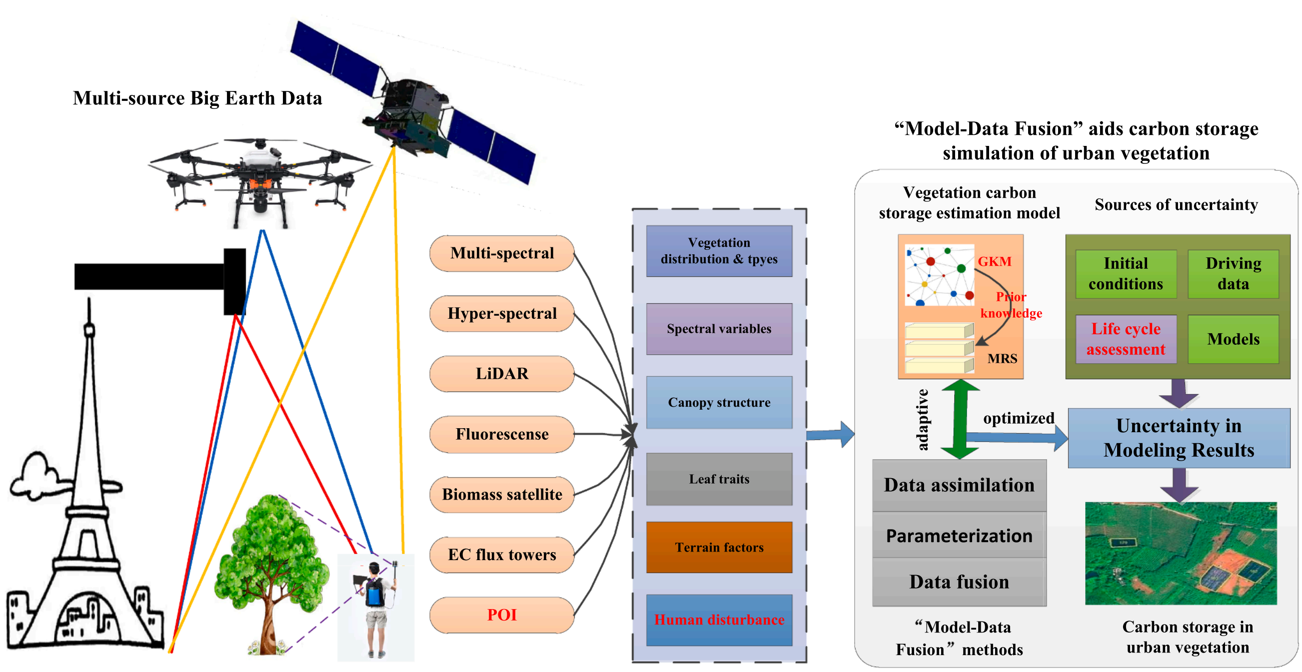

Fig. 5. A conceptual overview of multisource Big Earth Data incorporated with "Model-Data" methods to reduce the simulation uncertainty in UV carbon storage. Note: POI, point of interest; GKM, geological knowledge mapping; MRS, model representation symbols.

vegetation; 2) improving key nodes of the earth observation sensor network, especially the distribution of EC flux towers in urban settings; 3) leveraging the "Model-Data Fusion" technology by integrating big earth data and carbon estimation models. We believe the envisioned research directions have the potential to better understand UV structure and carbon sequestration capacity and allow for a better understanding of UV in terrestrial ecosystems.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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