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FLUXNET Towards a Better Understanding of Global GHG Fluxes

Flux Footprints: A Critical Link to Bridge Eddy-Covariance Measurements With Models, Remote Sensing, and Other Observations

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ABSTRACT

Global networks of eddy-covariance flux towers play a pivotal role in enhancing our predictive understanding of carbon and water cycling of biological systems in response to regional and global environmental change. Despite their broad application in numerous studies, the spatial aspects of the flux measurements have often been ignored or treated ambiguously, thereby remaining a primary source of uncertainty. The area contributing to the flux—referred to as the flux footprint—varies over time depending on wind direction, atmospheric turbulence, effective measurement heights, surface characteristics, and mesoscale forcings. The footprint dynamics, along with underlying source-sink heterogeneity, lead to spatial and temporal variability in the sensed fluxes, complicating the interpretation of flux data and their integration with a range of observations and models. This article addresses this critical link by reviewing the most up-to-date research, identifying knowledge gaps and challenges, and pointing out future research needs and opportunities. We begin with an overview of the current state of footprint modeling and its applications, from single-site studies to large-scale syntheses, summarizing how flux footprints have been used to interpret spatial flux variability and to integrate flux data with models, remote sensing, and other observations. We highlight how this critical spatial aspect could complicate the processing of eddy-covariance fluxes, the definition of mass and energy continuity, and the interpretation of flux response functions and parameters, all of which have significant implications for numerous applications and research. We then point out potential opportunities and future research needs to bridge this knowledge gap, highlighting both readily available and prominent emerging ones. We conclude by urging the scientific community to (re)consider the spatiotemporal dynamics of eddy-covariance flux measurements, and to investigate and evaluate potential approaches across scales, applications, and disciplines.

1 | Introduction

Global networks of eddy-covariance flux towers and numerous research studies built upon them over the last three decades have been the cornerstone of promoting our understanding of the interface between biological systems and current environmental change at regional, continental, and global scales (D. D. Baldocchi 2003, 2008, 2014, 2020; Xiao et al. 2025). The biogeochemistry and ecology communities have utilized flux and various ancillary data to understand ecosystem carbon, water, and energy cycles, as well as their responses to current and future climates across biomes (Yi et al. 2010; Wolf et al. 2016; Duffy et al. 2021; Knox et al. 2021; Migliavacca et al. 2021). The direct, continuous, and non-destructive measurements enable the construction of high-precision carbon and water budgets from hourly to decadal scales, supporting a broad range of applications such as those of nature-based climate solutions, resource management, greenhouse gas inventory, water distribution, and agriculture practices (Runkle et al. 2017; Hemes et al. 2019; Aguilos et al. 2021; Hollinger et al. 2021; Melton et al. 2022). Large-scale flux datasets (e.g., AmeriFlux, FLUXNET) have been widely used to benchmark, validate, and improve Earth System Models and various process-based models (Friend et al. 2007; Williams et al. 2009; Bonan et al. 2012; Chen et al. 2018; Collier et al. 2018). Remote-sensing- and machine-learning-based research utilizes large-scale flux data to train, parameterize, and validate models for upscaling carbon and water fluxes in both space and time (Xiao et al. 2014; Verma et al. 2015; Jung et al. 2019; McNicol et al. 2023; Nelson et al. 2024). Spatially gridded fluxes from the aforementioned modeling approaches are essential for understanding and predicting the vulnerability and resilience of biological systems in response to environmental changes from local to regional, continental, and global scales (Beer et al. 2010; Li et al. 2018, 2023; Yuan et al. 2024; Kang et al. 2025; Losos et al. 2025).

Across the applications and disciplines discussed above, eddy-covariance flux data are widely recognized and utilized for their rich temporal information. In contrast, their spatial aspects are often overlooked or treated ambiguously, remaining a primary source of uncertainties (Xu, Metzger, and Desai 2017; Metzger 2018; Chu et al. 2021). Briefly, the source area contributing to the flux—referred to as the flux footprint—varies from time to time depending on the wind direction, turbulent state of the atmosphere, effective measurement heights, underlying surface characteristics, and mesoscale forcings (Schmid 2002; Vesala et al. 2008; Rannik et al. 2012) (Figure 1, left panel). Despite the community's efforts and best practices in establishing flux towers in ideally homogeneous environments, few sites are located in truly homogeneous landscapes (Griebel, Metzen, Pendall, et al. 2020; Stoy et al. 2013). Additionally, numerous studies have demonstrated that fine-scale gradients or hotspots of fluxes can form due to variability driven by species composition, canopy structure, subsurface biogeochemistry, hydrological gradients, salinity, nutrient availability, soil characteristics, and microtopography (Chasmer et al. 2008; Griebel et al. 2016; El-Madany et al. 2018; Shahan et al. 2022). Consequently, the footprint dynamics and underlying source-sink heterogeneity jointly lead to spatial and temporal variability in the sensed fluxes, complicating the interpretation and integration of flux data with other observations or models, which typically assume

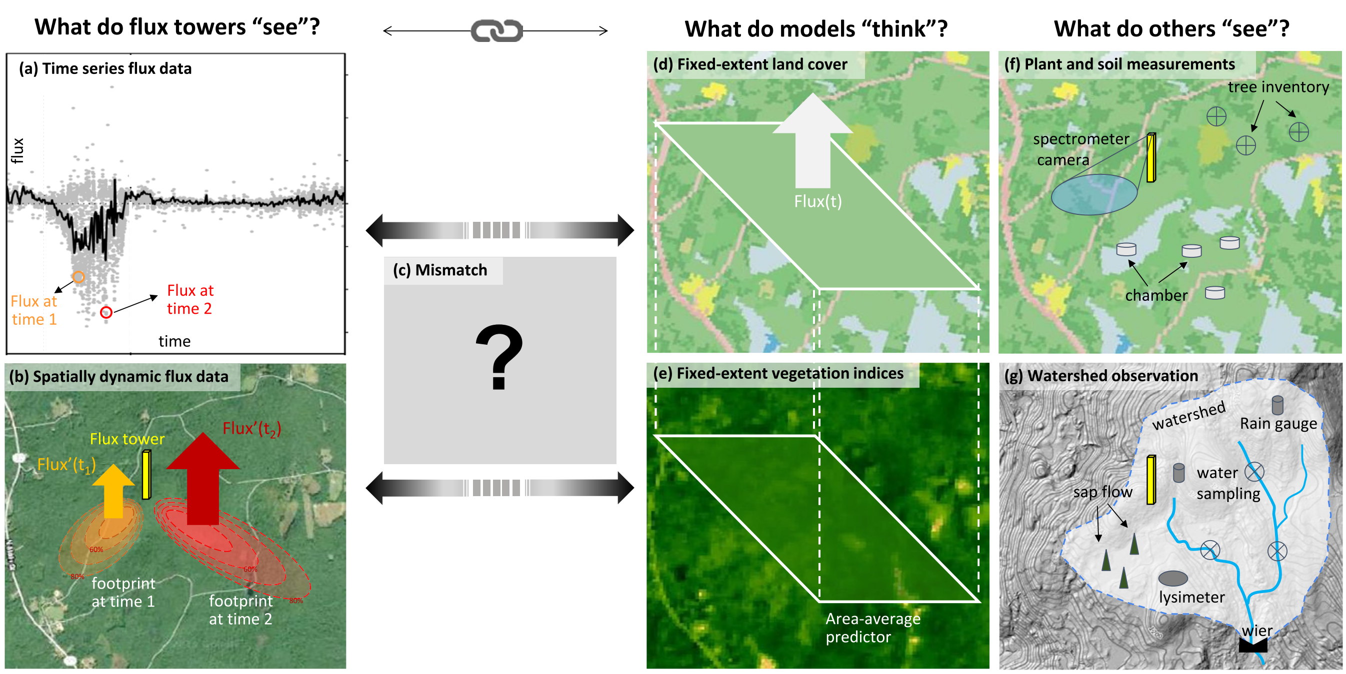

FIGURE 1 | A concept diagram of the missing link integrating flux data with other models, remote sensing, spatially gridded products, or observations. Panel (a) shows the commonly recognized flux time series, while Panel (b) exemplifies the corresponding source areas that contribute to two selected data points, i.e., the modeled flux footprints. The contours in Panel (b) enclose 50% (innermost), 60%, 70%, and 80% (outermost) of the source/sink contributions. Panels (d, e) showed examples of remote sensing or spatially explicit models, which typically assume a fixed spatial extent or known component composition. Panels (f, g) showed examples of vegetation, soil, and hydrological observations, along with their spatial extents or fields of view. The spatiotemporal dynamics of flux measurements complicate the integration between flux data and other models or observations (c).

a static spatial domain (Figure 1, right panel). Important questions emerge from these ongoing discussions: How do the spatial dynamics complicate the interpretation of fluxes? How prevalent is this issue across sites? To what extent will this mismatch bias the integration with other observations and models? What are the available or potential approaches to mitigate or resolve this issue?

This article addresses the questions above by reviewing up-to-date research. We begin with an overview of the current state of footprint modeling (Section 2.1) and its applications in site-level case studies, including the interpretation of spatial flux variability (Section 2.2) and the integration of flux data with other observations (Section 2.3). We summarize previous approaches and their challenges in incorporating footprint information into large-scale syntheses (Section 3.1), integrating it with remote sensing or other spatially gridded data (Section 3.2), and benchmarking against forecasting or model assimilation (Section 3.3). We then highlight potential opportunities and future research needs in large-scale syntheses (Section 4.1), integration with models, remote sensing, and other observations (Section 4.2), and various approaches and emerging paradigms to reconcile the spatiotemporally dynamic flux data (Sections 4.3 and 4.4). We conclude with an overview of future directions (Section 5). We included the relevant publications to the best of our knowledge, but we recognize that this review does not constitute an exhaustive literature review.

2 | Current State of Footprint Applications

2.1 | Advancement in Footprint Models

The concept that flux measurements represent some portion of the surface upwind of the measurement sensors has been recognized since the earliest development of the eddy-covariance technique. However, the formalization of flux footprints began to appear in the literature with the work of Schmid and Oke (1990) and Leclerc and Thurtell (1990), the latter who first coined the term "footprint function" (Leclerc and Foken 2016). That means, the source area contributing to the flux at any measurement time can be expressed as a function of wind, turbulence, and surface characteristics (Schmid 2002) (Figure 1b). Many footprint models have been developed over the years (Rannik et al. 2012; Leclerc and Foken 2014; Sogachev and Repina 2025). In general, footprint models can be categorized by dimension and theoretical derivation, ranging from simple analytical models (Leclerc and Thurtell 1990; Schmid and Oke 1990; Schuepp et al. 1990; Schmid 1994) and analytical parameterizations (Hsieh et al. 2000; Kormann and Meixner 2001; Kljun et al. 2004, 2015; Detto et al. 2006), to more sophisticated simulations that account for complex environmental variables, such as Lagrangian Stochastic models (e.g., forward trajectory (Leclerc and Thurtell 1990), and backward trajectory (Kljun et al. 2002)) and Large-Eddy-Simulation models (Leclerc et al. 1997; Steinfeld et al. 2008; Leclerc and Foken 2014). In particular, the development of analytical models or parameterizations has enabled footprints to be calculated routinely over long records and across many sites (Hsieh et al. 2000; Kormann and Meixner 2001; Kljun et al. 2015), thereby boosting large-scale applications that utilize footprint information (Chu et al. 2021). Despite advancements in model development, model benchmarking and experimental validation remain an active research area, often limited to individual case studies (Arriga et al. 2017; Heidbach et al. 2017; Nicolini et al. 2017; Dumortier et al. 2019; Kumari et al. 2020). Most footprint models follow assumptions similar to those used in calculating eddy-covariance fluxes, such as stationarity, homogeneity of roughness elements and flux sources, and sufficient turbulent mixing. In practice, few tower sites strictly adhere to these ideal conditions at all times (Griebel, Metzen, Pendall, et al. 2020). The potential bias or error in footprint prediction under less-ideal conditions becomes practically important but remains unknown or unreported in most case studies. The ongoing or future development of footprint models should continue to refine their accuracy and applicability, addressing unresolved questions about the quantification or parameterization of measurement height, surface roughness, and the influence of complex terrains (Finnigan 2004; Sogachev et al. 2005; Foken 2017; Liu et al. 2024).

2.2 | Interpreting Spatial Flux Variability Using Footprints

Footprint analyses provide a critical link between measured fluxes and the sources and sinks of the trace gases, water vapor, and energy. Amiro (1998) first introduced the concept of footprint climatology, calculated from footprint-weighted flux contributions over a target period. The resulting climatology, rather than a collection of hourly footprints, enables researchers to delineate areas of flux contributions, providing a practical link between fluxes and surface characteristics. Several studies have adopted this idea and further expanded its applications. For example, studies have used footprints to explain the flux dynamics due to contributions from different land covers (Wang et al. 2006; Biermann et al. 2014; Helbig et al. 2017; Buzacott et al. 2024; Yan et al. 2025), crop types (Barcza et al. 2009; Hernandez Rodriguez et al. 2023; Kumari et al. 2024), forest patches (Chen et al. 2009; Chi et al. 2019; Griebel, Metzen, Boer, et al. 2020), cattle activities (Hörtnagl et al. 2018; Stoy et al. 2021), small-scale disturbance or management (Pinnington et al. 2017; Fenster et al. 2023), ecosystem structural and physiological variability (Oren et al. 2006; Chasmer et al. 2008; El-Madany et al. 2018).

Over the past few decades, research and societal needs have fostered the establishment of more flux towers in wetlands. With inherent heterogeneity in hydrology, salinity, vegetation, and microtopography, wetlands often exhibit evident heterogeneity in flux sources and sinks (Baldocchi et al. 2012; Matthes et al. 2014; Morin et al. 2017; Rey-Sanchez et al. 2018; Tuovinen et al. 2019; Hao et al. 2025). Footprint analyses have emerged as a crucial and necessary tool, enabling the attribution of flux contributions from microhabitats and the identification of potential hotspots (Matthes et al. 2014; Morin et al. 2017; Noumonvi et al. 2025; Tikkasalo et al. 2025). Notably, few studies have highlighted that CH_4 hotspots can form as a result of spatial heterogeneity in belowground biogeochemical and microbial processes, which may not be readily visible or detectable from aboveground land cover types or other surface characteristics (Chamberlain et al. 2018; Hartman et al. 2024; Rey-Sanchez et al. 2025). To some extent, raising instrument heights to ensure sufficient footprint coverage may increase the probability of sampling spatial heterogeneity and obtaining representative fluxes. However, several studies have shown that seasonal dynamics in hydrology and vegetation cover can alter the spatial pattern of CH_4 emissions over time, highlighting the need to account for temporally dynamic footprints when interpreting fluxes at wetlands (Rey-Sanchez et al. 2018, 2022; Hill and Vargas 2022). Lastly, several studies have stressed the significant biases in the annual/seasonal flux budgets when ignoring spatial heterogeneity and footprint dynamics, which can lead to 14%–25% biases in area-integrated fluxes (Matthes et al. 2014; Rey-Sanchez et al. 2018; Tuovinen et al. 2019) and up to 83%–100% in extreme cases (Fox et al. 2008; Morin et al. 2017; Ludwig et al. 2024).

In intensively managed agricultural systems, footprint analyses have been used to quantify the flux contributions of different crop types or agricultural practices (Soegaard et al. 2003; Barcza et al. 2009; Mukherjee et al. 2015; Wiesner et al. 2022; Hernandez Rodriguez et al. 2023; Kang et al. 2023). Spatial organization, such as alternative farming, row cropping, or cover crops, can lead to recurring source-sink distributions and ultimately, wind-direction dependency in flux signals (Wiesner et al. 2022; Callejas-Rodelas et al. 2024). N_2O fluxes, in particular, are highly relevant because hot spots and hot moments dominate the majority of total emissions (Wagner-Riddle et al. 2020). While eddy-covariance N_2O measurements remain an active research area (Jordan Bureau et al. 2017; Wall et al. 2023; Li et al. 2026), studies based on flux-gradient and chamber measurements have shown high spatiotemporal variability (Waldo et al. 2019). Similar to CH_4 fluxes, N_2O source-sink heterogeneity is often driven by microbial and biogeochemical processes belowground and may not reflect the observable landscape features (e.g., land cover, vegetation types) discussed above.

Urban areas are especially challenging for the eddy-covariance method due to their highly heterogeneous nature. In addition, there is a high likelihood that measurements may be influenced by nearby point-source pollution from traffic, industry, or heating (Hiller et al. 2011; Kotthaus and Grimmond 2012; Horne et al. 2026). Thus, eddy-covariance measurements in urban areas are typically conducted on tall towers with measurement heights well above the urban canopy, thereby increasing the contribution of larger, lower-frequency eddies and the uncertainty in storage and advection (Grimmond and Oke 1999; Nordbo et al. 2012; Bjorkegren et al. 2015). In this environment, multiple flux towers and measurements at various heights or locations are frequently deployed to monitor contrasting land use sectors or to reduce random and systematic uncertainties in flux estimates. Flux footprint analyses are essential for attributing flux dynamics and interpreting annual budgets (Järvi et al. 2018; Vulova et al. 2021; Ueyama and Takano 2022; Chen et al. 2023a).

2.3 | Matching Flux With Other Observations

Footprint analyses are essential, or even inevitable, when pairing flux measurements with other observations, because they provide a crucial link that delineates the source areas and justifies the spatial matches. We briefly summarize examples below from chambers, hydrology, hyperspectroscopy, and other micrometeorological measurements.

Chamber measurements have been used for decades to study fluxes at the plot or organism scales (Dore et al. 2003; Zhang et al. 2012). One common application was to use chamber measurements to examine or verify flux variation within the tower footprints and the controlling factors (Forbrich et al. 2011; Hill and Vargas 2022; Guo et al. 2025) (Figure 1f). For example, Darenova et al. (2016) assessed the spatial variability of soil CO_2 efflux across four ecosystems: spruce forest, beech forest, grassland, and wetland. They found that the grassland had the lowest spatial variability, while the wetland had the highest. They also found that the drivers of CO_2 efflux varied across ecosystems. There were numerous efforts to match scales between chamber- and tower-based fluxes (Schrier-Uijl et al. 2010; Poyda et al. 2017; Chaichana et al. 2018), but these remained challenging due to uncertainties inherent in both techniques, natural variability, and the scaling process (Yildiz et al. 2025). An emerging approach is to use chamber measurements as an independent constraint to reconcile or decompose the tower-based fluxes. For example, Morin et al. (2017) combined eddy-covariance and chamber flux measurements to develop a scaling approach for partitioning tower-based CH_4 fluxes into contributions from patches over a small, heterogeneous wetland. Several subsequent studies have sought to further improve the approach (Rey-Sanchez et al. 2018). Notably, while focusing on chamber measurements here, we recognized that similar efforts and challenges exist for those combining flux towers with small-scale flux or storage observations, such as lysimeters, sap flows, and tree/soil inventory (Wilson et al. 2001; Ehman et al. 2002; Oishi et al. 2008; Chamberlain et al. 2018; Kannenberg et al. 2019; Stoy et al. 2019; Bian et al. 2024).

The hydrology community has a long history of combining tower-based evapotranspiration with other watershed measurements (e.g., precipitation, runoff, streamflow) (Amiro 1998; Wilson et al. 2001; Scott 2010; Anderson and Vivoni 2016) (Figure 1g). While not all studies explicitly perform footprint analyses, they generally assume known tower footprints and address the spatial mismatches among techniques and inherent variability in the watershed (Anderson and Vivoni 2016; Schreiner-McGraw et al. 2016). Another emerging research area is the integration of tower-based carbon fluxes with lateral hydrologic carbon flows in attempts to construct the net ecosystem carbon balance (Chapin et al. 2006), mainly in wetlands (Chu et al. 2015; Malone et al. 2021; Santos et al. 2021; Beckebanze et al. 2022). Here, footprint analyses become an essential interface to reconcile the fluxes from both approaches with distinct source areas. The lateral carbon fluxes typically encompass particulate/dissolved organic carbon, dissolved CO_2 and CH_4, whose sources and sinks can vary across wetland types (Wang et al. 2016; Chu, Wang, et al. 2018; Tamborski et al. 2021). Also, the spatial extent to which the lateral fluxes influence largely depends on the hydrological events (e.g., tides, channel flow, streamflow, groundwater seepage). As we begin to integrate eddy flux measurements with other measurements at different spatial scales (Tokoro et al. 2014; Bogard et al. 2020; Chi et al. 2020), accounting for footprint variation will be crucial for determining the carbon and water balances.

Integrating hyperspectral or LIDAR observations with flux footprint analyses provides a novel approach to examining spatial heterogeneity and improving the attribution of fluxes to land-surface features (Gamon 2015; Pierrat et al. 2025). A few studies have used airborne imaging spectroscopy to detect fine-scale surface reflectance, linking its variation with flux footprints to better understand gross primary productivity in semiarid ecosystems with mixed tree-grass canopies (Pacheco-Labrador et al. 2017; DuBois et al. 2018; El-Madany et al. 2018). Similar studies extended this approach to superscale (e.g., ~10^0–$10^2\,m^2$) vegetation indices derived from commercial satellite systems such as CubeSat, WorldView, or IKONOS (Kim et al. 2006; Giannico et al. 2018; Kong et al. 2022), airborne platforms (Simpson et al. 2021; Yazbeck, Schlutow, et al. 2025), tower-based hyperspectrometers (Damm et al. 2010; Balzarolo et al. 2011; Pierrat et al. 2024, 2025), or cameras (Yan et al. 2019; Javadian et al. 2024) (Figure 1f). In parallel, several studies used LIDAR-derived biometrics to characterize forest structural heterogeneity and to attribute its effects on spatial source-sink variability (Chasmer et al. 2011; Griebel, Metzen, Boer, et al. 2020). By matching remote-sensing data with flux footprints, these studies showed significant improvement in the interpretation and prediction of fluxes, particularly in ecosystems with inherent complexity. Going forward, we urge the research community to coordinate campaigns that combine flux measurements with tower-, drone-, aircraft-, and satellite-based hyperspectral observations, embedded within a footprint modeling framework. These efforts will not only improve flux attribution at the site level but also facilitate upscaling strategies for network-wide synthesis and model evaluation (Ryu 2024).

Footprint analyses are particularly essential for experiments that deploy multilevel or multi-tower eddy-covariance measurements (Wang et al. 2006; Hill et al. 2017; Chi et al. 2020; Cunliffe et al. 2022). For example, studies have strategically deployed multilevel eddy-covariance measurements, leveraging their different footprint areas and underlying surfaces to differentiate flux contributions from the land-cover mosaic (Wang et al. 2006; Helbig et al. 2016; Klosterhalfen et al. 2023). Another example was the use of below-canopy eddy-covariance measurements to separate overstory and understory contributions (i.e., from the vegetation and the soil) and partition the component fluxes of gross primary production and transpiration of the tree canopy (van Gorsel et al. 2011; Thomas et al. 2013; Jocher et al. 2017, 2018; Paul-Limoges et al. 2017, 2020). Forest ecosystems are structurally complex, with distinct vertical layers and functional properties below, within, and above the canopy (Misson et al. 2007). Concurrent above- and below-canopy eddy-covariance measurements are a promising approach to overcoming these limitations and are increasingly being applied across flux networks (Sulman et al. 2016; Perez-Priego et al. 2018; Chi et al. 2021; Wolf et al. 2024). However, the apparent mismatch in footprint extents can introduce sampling bias in source areas, complicating the interpretation of flux differences. Furthermore, most analytical footprint models were not developed for application within tree canopies, where understory vegetation and tree trunks break apart turbulent eddies irregularly and more rapidly than above the canopy (D. Baldocchi 1997). Further evaluations and developments are needed to investigate the applicability of established footprint models in such below-canopy locations. Lastly, while focusing on eddy covariance, we recognize that the footprint concepts apply to other micrometeorological flux measurements (e.g., flux gradient, surface renewal, Bowen-ratio method (Horst 1999; Waldo et al. 2019; Wang et al. 2023)). Depending on the nature of the measured quantities (e.g., concentration, turbulence), those methods may have flux footprints that differ from those of eddy covariance (Leclerc and Foken 2014). Yet, most micrometeorological methods share similar assumptions and spatiotemporal dynamics as discussed above. Thus, similar consideration about their source areas should be given when integrating across methods.

3 | Footprint Applications for Large-Scale Syntheses and Modeling

3.1 | Flux Interpretation and Uncertainty

While site-specific approaches to tackle the footprint challenge at known heterogeneous sites are increasingly applied, standardized and coordinated initiatives to quantify heterogeneity and address systemic errors across the flux networks still lag behind. Several cross-site synthesis activities have assessed the footprint heterogeneity and representativeness of flux towers across networks (Göckede et al. 2008; Chen et al. 2012; Ran et al. 2016; Chu et al. 2021; Fang et al. 2024). While varying in implementation details, they generally adopted certain spatial surrogates (e.g., vegetation indices, modeled fluxes) to represent the spatial variability of flux sources and sinks. They then evaluated the potential source-sink similarity between the footprints and designated fixed areas surrounding each tower, providing a prognostic assessment of the footprint representativeness. These studies revealed the various heterogeneity across sites and emphasized the need to carefully consider each site's footprint representativeness when using large-scale flux datasets, such as AmeriFlux and FLUXNET. However, despite the insights gained from these efforts, they fell short of providing direct links between footprint heterogeneity and flux variability as in the site-level case studies (Section 2.2). In practice, there are no standardized, continuous, and large-scale footprint data products, which hinders the broad application of footprints in large-scale synthesis and modeling research.

There have been several intensive field campaigns investigating the direct relationships among source-sink heterogeneity, footprints, and flux variability by accounting for additional flux transport terms influenced by site heterogeneity, including advective and dispersive fluxes. For example, the LAFE campaign quantified land-atmosphere feedback through comprehensive measurement networks that integrate vertical and horizontal transport diagnostics (Wulfmeyer et al. 2018). The IPAQS 2019 field campaign extended this effort to desert environments, showing that three-dimensional energy-balance assessments significantly outperform traditional one-dimensional methods (Morrison et al. 2023). The recent CHEESEHEAD19 campaign deployed a cluster of flux towers and ancillary observations within the footprint of a tall tower in a $10^2\,km^2$ domain. The studies demonstrated how heterogeneous landscapes generate mesoscale circulations and flux divergence, severely complicating energy balance closure (Butterworth et al. 2021). Together, these studies provided direct links between the underlying heterogeneity and the measured fluxes, emphasizing the risks in misrepresenting actual surface-atmosphere exchange processes when neglecting landscape-scale heterogeneity and transport variability. More work is required to develop ways to generalize the findings from these campaigns and scale up implementation to the network level, for example, by incorporating heterogeneity scaling factors or additional parameterized terms.

One critical gap remains regarding the extent to which footprint variability and representativeness across hundreds or thousands of flux towers can bias the interpretation of large-scale flux data products, such as FLUXNET. For example, annual carbon or water budgets derived from flux measurements are crucial for supporting greenhouse gas accounting and water management. They are typically calculated by summing all half-hourly flux data, whether measured or gap-filled, across the desired time interval, assuming uniform spatial sampling across the flux footprint (Kim et al. 2020; Pastorello et al. 2020). A related, yet poorly understood source of uncertainty concerns the commonly adopted nighttime-based partitioning method for gross primary production and ecosystem respiration (Reichstein et al. 2005), which also assumes that daytime and nighttime flux measurements represent functionally similar underlying surfaces. However, these assumptions may not hold depending on a site's underlying spatiotemporal source-sink variability, as well as the footprint dynamics due to wind direction, atmospheric stability, and other meteorological factors (Montaldo and Oren 2016; Griebel, Metzen, Pendall, et al. 2020; Montaldo et al. 2020; Rey-Sanchez et al. 2022; Klosterhalfen et al. 2023; Hawman et al. 2024). Combined together, these variabilities can introduce systematic bias into annual flux budgets, complicating the interpretation and comparability of flux budgets across sites and years, as well as their comparison with other methods. A recent synthesis assessed this potential bias across 154 FLUXNET sites and found that no site was truly homogeneous, and only a very few were sampled consistently across wind sectors over the years (Griebel, Metzen, Pendall, et al. 2020). They further proposed a space–time equivalent approach that explicitly accounts for spatiotemporal sampling variability to provide representative annual carbon estimates. They estimated that conventional annual carbon budget calculations were biased by ~10% on average across all sites, with a wide range of +13% in savannas to −35% in wetlands. These systematic biases are particularly consequential for applications that rely on flux data to support greenhouse gas accounting, ecosystem service assessment, or natural resource management.

Another poorly understood aspect is how spatially dynamic footprints may complicate the fundamental mass and energy continuity. Typically, the eddy-covariance technique assumes spatial homogeneity and steady-state conditions, allowing users to simplify the mass and energy balance equations using a fixed, defined control volume (e.g., Finnigan et al. 2003, 2004, 2008; Foken 2017; Lee et al. 2004). In real-world observations where there is no true homogeneity, the violation of this assumption (to varying degrees across sites) may lead to "missing flux" due to landscape heterogeneity and transport divergence (Foken 2017). Studies have suggested that this mechanism may be a major cause of surface energy imbalance, on the order of 20%–40% (Stoy et al. 2013; Butterworth et al. 2024; Wanner et al. 2024; Wang et al. 2024).

3.2 | Footprint Integration With Remote Sensing and Spatial Gridded Data

Over the last few decades, eddy-covariance flux data have been widely used to train, calibrate, and validate process-based or data-driven models along with remote-sensing and spatially gridded data, with the ultimate goal of upscaling fluxes beyond the footprints (Xiao et al. 2019; Lucarini et al. 2024). With a strong spatial focus, most of these studies recognized the importance of matching the potential source areas of flux measurements and other spatial data. They adopted various approaches to account for the spatial matching.

Since the early 2000s, flux networks have served as the core infrastructure of the Earth Observing System (EOS) for global terrestrial vegetation monitoring (Running et al. 1999). Numerous studies attempted to utilize spatially moderate-resolution (e.g., ~10^5–$10^6\,m^2$) remote-sensing data (e.g., Moderate Resolution Imaging Spectroradiometer [MODIS], Advanced Very High Resolution Radiometer [AVHRR]) and models to extrapolate fluxes from flux tower locations to regions and the globe (Beer et al. 2010; Jung et al. 2011, 2019; Xiao et al. 2014). Those studies typically prescribed a fixed cutout of remote-sensing pixels (e.g., 1×1, $3\times3\,km^2$) surrounding the tower locations and assumed that these areas represented the flux footprints across sites (Heinsch et al. 2006; Verma et al. 2015; Zhang et al. 2017; Badgley et al. 2019). Two issues may result from this fixed-cutoff approach. First, the selected pixels may not overlap or adequately represent the flux footprints, particularly at sites with limited fetches (e.g., short towers) or unevenly distributed wind directions. Second, the assumption of source-sink homogeneity across the selected pixels may not hold, particularly for inherently complex or patchy ecosystems (e.g., wetlands, semiarid biomes, and croplands) (Chasmer et al. 2011; Nelson et al. 2020; Dannenberg et al. 2023; Hernandez Rodriguez et al. 2023; McNicol et al. 2023; Ying et al. 2025). These issues can be particularly critical for data-driven upscaling studies, in which the models were trained solely on flux data and assumed colocated remote-sensing and spatially gridded datasets. Any bias introduced by the spatial mismatches will propagate into subsequent processes (Gaber et al. 2024; Kang et al. 2025).

Separate efforts were made to match flux tower data with spatially fine-resolution (e.g., ~10^2–$10^4\,m^2$) remote-sensing data (e.g., Landsat, Sentinel, ECOSTRESS). At a relatively finer scale, it became feasible to match the flux footprints even at sites with limited fetches (Figure 2). Some studies have adopted a prognostic approach, pairing flux data with land surface characteristics of carefully selected pixels, based on the prevailing wind direction and estimated source areas (DuBois et al. 2018; Fisher et al. 2020; Volk et al. 2023). A few studies have further explored spatiotemporally explicit methods that incorporate footprint information (e.g., monthly climatology) into their model training and validation frameworks (Chen et al. 2010; Fu et al. 2014; Ran et al. 2016; Xu, Wang, et al. 2017; Junttila et al. 2021; Huang et al. 2022; Zhuravlev et al. 2022; Goodwell et al. 2025). Recent advances in remote-sensing technology offer new opportunities

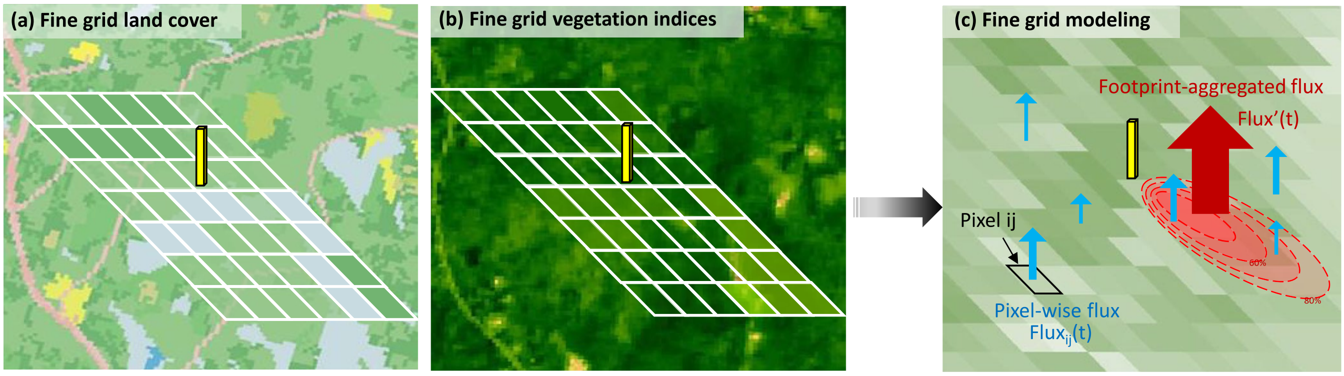

FIGURE 2 | A concept diagram of overcoming footprint mismatches through a fine-grid modeling approach (c). The approaches use fine-resolution remote sensing and spatially gridded products (a, b) to strategically align the model extents with the flux footprints at the target time intervals.

to address the spatial mismatch problem. Super-resolution (e.g., ~10^0–10^2 m^2) remote-sensing products from mostly commercial satellite (e.g., PlanetScope, CubeSats, WorldView, IKONOS) or airborne platforms (e.g., aircraft, drones) now enable resolving the detailed spatial composition and heterogeneity (e.g., tree crown, wetland patches, shrub-grass mosaic) within flux footprints (El-Madany et al. 2018; Wang et al. 2019; Griebel, Metzen, Boer, et al. 2020; Kong et al. 2022; Revenga et al. 2024; Williams et al. 2025; Noumonvi et al. 2026). These advancements largely enhance the spatial match between remote-sensing pixels and flux footprints, ultimately improving model performance.

Limited, yet critical efforts have been undertaken to fully address the spatiotemporal matching between flux footprints and remote-sensing data. In theory, the flux footprints vary from hour to hour, spanning spatial scales of ~10^3–10^7 m^2. To fully resolve the spatiotemporal dynamics, it requires remote-sensing and other spatially gridded products to match both the spatial and temporal scales, which remains challenging to achieve. Thus, most studies utilizing spatially fine- or super-resolution remote sensing, as mentioned above, had to compromise on temporal matching, either by using daily, weekly, or monthly aggregated footprints or by down-selecting flux data for only the relatively infrequent overpassing periods. Similarly, compromises were made for spatial matching for studies that utilized geostationary satellites with temporally fine but spatially coarse resolutions (Ranjbar et al. 2024). Recent advances in data fusion enable the creation of remote-sensing data products with high spatial and temporal resolutions from multiple sources, highlighting a promising yet underexplored approach to addressing this knowledge gap (Anderson et al. 2007; Zhong et al. 2019; Desai et al. 2021).

3.3 | Footprints in Forecasting and Model Assimilation

Earth system models, ecosystem models, and near-term ecological forecasting continue to advance in capability. Eddy-covariance flux data played a crucial role in benchmarking and improving the model performance (Hoffman et al. 2017; Xiao et al. 2025). Unlike remote-sensing research discussed above, most of these process-based models have coarse or implicit spatial extents. Thus, model-data benchmarking studies were mostly carried out using point-scale simulations at individual flux tower sites (Bonan et al. 2012; Chaney et al. 2016). Often, the dominant plant function type and soil characteristics at the flux tower site was used to prescribe model parameterization (Chen et al. 2018). In some cases, model simulations used forcings based on remote sensing or reanalysis climate drivers from the nearest grid cell, assuming they represented the areas covered by the flux tower footprints (Ricciuto et al. 2018; Buotte et al. 2019; Stoy et al. 2026). Studies suggested that these coarse-approximation approaches may be insufficient for assessing model performance (Hoffman et al. 2017; Durden et al. 2020). This issue is particularly pronounced in ecosystems with mixed plant functional types and in models with strong nonlinearity between parameters and modeled fluxes (Wang et al. 2001; Santaren et al. 2007). A growing list of case studies has attempted to address this challenge by incorporating mixed functional groups or spatial heterogeneity into the model framework (Pinnington et al. 2017; Wang et al. 2022; Yazbeck et al. 2024; Yazbeck, Bohrer, et al. 2025; Moutahir et al. 2025; Murphy et al. 2025). They showed that model-data benchmarking improved significantly in capturing flux dynamics driven by spatial heterogeneity.

The spatial mismatch between flux measurements and models leads to biases in benchmarking and hinders further improvements in model fidelity, calling for further actions to incorporate footprints into model evaluation frameworks, such as the International Land Model Benchmarking (ILAMB) system (Collier et al. 2018) or Protocol for the Analysis of Land Surface Models (PALS) Land Surface Model Benchmarking Evaluation Project (PLUMBER) (Best et al. 2015). Rather than assuming that flux measurements represent fluxes over a homogeneous grid cell, next-generation forecasts and model evaluations must consider the spatial heterogeneity embedded in the flux data, particularly by incorporating spatially dynamic flux footprints (Pinnington et al. 2017; Wang et al. 2022; Moutahir et al. 2025). Ultimately, this shift toward spatially resolved benchmarking will support the development of more robust, scalable, and reliable predictions of terrestrial ecosystem behavior in a changing climate.

An emerging yet potentially promising direction for incorporating spatial information embedded in flux measurements is to leverage deep learning architectures specifically designed to handle raster data, such as Convolutional Neural Networks (CNNs) (Vulova et al. 2021; Chen et al. 2023b; Zou et al. 2025).

These architectures enable models to systematically account for the spatial characteristics of fluxes and their corresponding footprints by considering not only pixel values but also the spatial relationships among pixels and their neighbors through convolutional operations. As a result, CNN-based and other spatially aware deep learning architectures offer a more realistic representation than traditional point-based models, which often neglect spatial information. For forecasting applications, spatially aware architectures, such as CNNs, can be combined with those designed for sequential data, such as Recurrent Neural Networks (RNNs) or Transformer architectures. These hybrid models are particularly well-suited for spatiotemporal problems, including footprint and flux forecasting.

4 | Opportunities and Future Research Needs

4.1 | Applying Footprints Across Networks

We advocate using flux datasets with footprint awareness, accounting for both the temporal and spatial dynamics observed by eddy-covariance techniques. Ultimately, all flux datasets should be provided and distributed along with standard and continuous footprint information, which requires joint efforts from the individual site teams, regional data repositories, and different user groups. Next, we discuss the key areas for future synergistic efforts.

First, the next generation of the FLUXNET dataset should include footprint information. FLUXNET, a joint effort among regional networks, has been at the forefront of harmonizing and standardizing flux data over the last several decades (e.g., Marconi Dataset, Falge et al. 2005; “La Thuile Synthesis Dataset” 2007; FLUXNET2015 Dataset, Pastorello et al. 2020). In particular, the ONFlux (Open Network-Enabled Flux) processing pipeline, jointly developed by the regional networks, enabled the regular generation of standardized FLUXNET datasets (e.g., FLUXNET2015, FLUXNET2025) across hundreds of sites (Papale 2020; Pastorello et al. 2020). We advocate that the ONEFlux processing pipeline should incorporate a footprint module to support the standardized footprint product.

Second, future research is needed to benchmark footprint models and conduct experimental validation, particularly across sites with varying terrain, canopy, turbulence regimes, and source-sink distributions (Rannik et al. 2012). Most widely used footprint models were developed for ideal conditions (e.g., steady-state conditions, horizontally homogeneous turbulence field). Practically, very few sites can meet these requirements at all times. Thus, a robust and transparent quantification of uncertainty is as critical as quantifying footprints (Stoy et al. 2021). The sources of uncertainty could arise from the models themselves and from random or systematic errors in the input data (e.g., magnetic declination in wind directions, canopy heights, or roughness).

Third, specific required wind statistics (e.g., the standard deviation of lateral wind velocity) for footprint calculations are less commonly computed and shared across flux networks, particularly from the early measurement decades. We recommend that these variables be (re)calculated and provided whenever possible. In the meantime, future efforts should focus on building surrogate models, whether theoretical or empirical (Beljaars et al. 1983; Chu et al. 2021), to fill these data gaps. Future discussions among the communities are highly encouraged to explore whether or how to estimate footprints when data gaps exist in certain input variables (Searcy et al. 2025).

Fourth, footprint calculations are sensitive to the effective measurement heights, which depend on the measurement height and canopy roughness. Ideally, accurate quantifications of canopy structures, both spatially and temporally, can be complemented by repeated LIDAR or inventory surveys. However, in practice, those observations are sparse, uneven, or non-standardized across the flux networks. A recommended practice is to calculate aerodynamic canopy heights using Monin-Obukhov similarity theory and wind data (Pennypacker and Baldocchi 2016). The method was later tested across AmeriFlux sites (Chu, Baldocchi, et al. 2018), demonstrating its utility particularly for sites experiencing dynamic canopy changes. Yet, caution should be exercised at sites with complex terrain, canopy, or flow regimes due to the method's underlying assumptions (see Chu, Baldocchi, et al. 2018, for details). Ideally, the derived aerodynamic canopy heights should be validated or calibrated using LIDAR or inventory data.

Lastly, we need more ancillary observations to attribute flux sources and sinks within the flux footprints and potentially validate footprint calculations. For example, co-located, continuous, and representative chamber measurements can help constrain or validate the flux decomposition within the flux footprints (Krauss et al. 2016; Morin et al. 2017; Shahan et al. 2022). Fine-resolution (both temporally and spatially) surface characteristics, such as vegetation indices, surface temperature, canopy structures, and soil moisture, can complement the interpretation or even attribution of flux variability within the footprints (Griebel et al. 2016; Xu, Metzger, and Desai 2017; El-Madany et al. 2018; Rey-Sanchez et al. 2022; Murphy et al. 2025).

4.2 | Matching Flux Footprints With Other Data and Models

Various approaches have been proposed to incorporate footprint information into a broader modeling framework. In this section, we summarize several readily available strategies that can be applied immediately and discuss a few emerging and potential research directions.

First, site-level representativeness metrics may be sufficient for specific applications with less spatially explicit requirements. Multiple synthesis studies have attempted to evaluate the site-level footprint representativeness and generate various representativeness indices across flux networks (Rebmann et al. 2005; Göckede et al. 2008; Chen et al. 2011, 2012; Ran et al. 2016; Chu et al. 2021; Fang et al. 2024). While varied in their targets, coverage, and techniques, the results can serve as a first-cut qualitative metric of each site's footprint complexity. For example, many process-based models focused on the dominant plant functional type or land cover type within the footprints. The site-level footprint-weighted vegetation composition may be sufficient to down-select sites with low inherent spatial heterogeneity and benchmark against their models using point-scale simulations (Williams et al. 2009; Bonan et al. 2012; Chaney et al. 2016; Chen et al. 2018). When applicable, modelers can explore the use of footprint-weighted vegetation composition to inform model setup and parameterization, thereby enabling a more realistic representation of ecosystem complexity (Yazbeck et al. 2024; Yazbeck, Bohrer, et al. 2025; Moutahir et al. 2025; Murphy et al. 2025).

Second, aggregated footprint climatologies (e.g., annual or seasonal) may be considered for research or applications that are less sensitive to temporal dynamics. At the time of writing, some data repositories (e.g., National Ecological Observatory Network [NEON], Integrated Carbon Observation System [ICOS]) or previous synthesis efforts (Chu et al. 2021; Fang et al. 2024) have published spatial datasets of footprint climatologies. While smoothing out fine-scale temporal variation, these aggregated footprints are sufficient to delineate the spatial extents in which the majority of flux contributions occur. The aggregated footprints may be the most practical and feasible option for applications that match flux data with observations over longer temporal scales (e.g., annual watershed budgets), particularly for sites with lower heterogeneity.

Third, several surrogates or modified footprint products have been proposed to alleviate the technical burdens of utilizing and interpreting full-scale, spatiotemporally dynamic footprints, which may be considered if they meet research and application needs. For example, windrose charts, which can be easily generated across flux networks, can serve as an alternative or preliminary analysis tool for large-scale modeling or synthesis research (DuBois et al. 2018; Fisher et al. 2020; Volk et al. 2023). Following a similar concept, Hernandez Rodriguez et al. (2023) proposed the fetch rose, a modification of the windrose that includes upwind distances (fetch) for each wind sector. This modified tool is a powerful and practical diagnostic for footprint quality control and for guiding data filtering or interpretation, particularly in parceled landscapes. Another approach is the footprint-weighted flux map (Amiro 1998; Mauder et al. 2008), which aggregates footprints over a target time frame, weighted by the flux magnitudes of each half-hour. The resulting maps thus provide the first approximation of the spatial distribution of sources and sinks within the footprints, identifying the potential hotspots (Rey-Sanchez et al. 2022). This approach is particularly resourceful for cases with substantial spatial variability, such as CH_4 fluxes in wetlands, to guide the fine-scale spatial sampling (e.g., chambers and porewater chemistry) (Rey-Sanchez et al. 2025).

Fourth, matching flux data with remote-sensing products remains an active research frontier (Ryu 2024). We discuss potential synergies and future directions in the next section (Section 4.3). In the near term, a hybrid, multi-tier approach may be the most feasible and practical option. We summarize them as follows: (1) Down-selecting sites based on the footprint representativeness information above is advised for applications relatively prone to spatial or temporal mismatches. This includes, but is not limited to, data-driven model training (Joiner and Yoshida 2020; Gaber et al. 2024; Kang et al. 2025), as well as studies in often patchy, fetch-limited landscapes (Fisher et al. 2020; Volk et al. 2023). (2) Pairing flux data with specific remote-sensing products of adequate resolution can be a practical strategy for sites with moderate heterogeneity. Spatially, forest flux towers typically have footprints of approximately 10^0–10^1 km^2 (Chu et al. 2021), allowing them to be paired with moderate-resolution remote-sensing products. Short-vegetation flux towers, particularly those located in patchy or heterogeneous landscapes, require fine- or super-resolution remote-sensing products to resolve their footprints (Romero et al. 2026). Temporally, certain remote-sensing products (e.g., land surface temperature) showed faster temporal dynamics than others (e.g., leaf area index, canopy height). Different temporal resolutions of footprints (e.g., hourly, daily, weekly, seasonally) may be used to resolve the target temporal dynamics. (3) For sites with high spatial heterogeneity and temporal dynamics, a fully spatial–temporal-resolved approach will be needed to address the spatiotemporal dynamics as seen by the flux footprints. Recent advances in remote-sensing data fusion from multiple platforms opened up opportunities to tackle this mismatch (see details in Section 3.2).

4.3 | From Footprints to Real-World Continuity

Footprints provide a mechanistic entry point for addressing the challenge of integrating flux data with other observations, models, or applications that often operate at fixed, explicit spatiotemporal scales. Numerous research efforts have attempted to bridge this gap by rectifying the spatially dynamic flux data into a fixed spatial domain (Figure 3). While diverging in approaches, the common goal was to disentangle the spatial and temporal dynamics, attributing spatial variation to

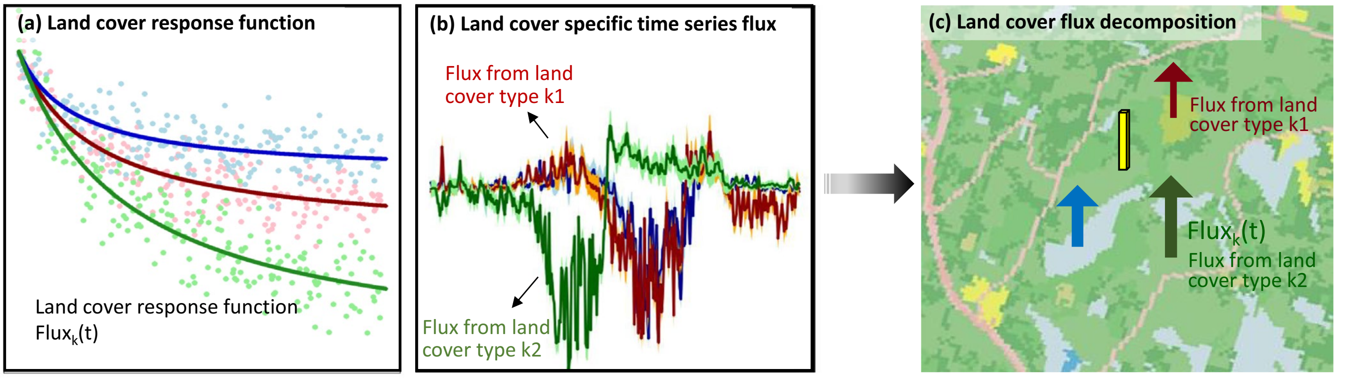

FIGURE 3 | A concept diagram of fully resolving footprint dynamics through a flux decomposition approach. Various approaches adopt different core models (a) to disentangle the fluxes into contributions from components within the footprints (b, c).

disaggregated spatial components, thereby enabling a better representation of the underlying processes of individual components, and ultimately generating a spatially consistent flux outcome to interface with real-world continuity (Metzger 2018; Novick et al. 2022; Falco et al. 2024). We briefly summarize those various efforts below.

Previous attempts all incorporated certain spatial constraints, but they diverged in their data types, structures, and scales. For example, several studies used spatial surface characteristics, either categorical (e.g., land covers, plant functional types (Tuovinen et al. 2019; Levy et al. 2020; Wiesner et al. 2022; Tikkasalo et al. 2025)) or continuous (e.g., vegetation indices, land surface temperature (Xu, Metzger, and Desai 2017; Wiesner et al. 2022)). This ancillary spatial information provides an indirect approximation of the source-sink magnitudes and distributions. On the other hand, a few studies used chambers to obtain direct flux measurements at targeted land-cover patches within the flux footprints (Morin et al. 2017; Rey-Sanchez et al. 2018). They used these snapshot measurements to define the relative flux strengths among patches, thereby constraining the decomposition of the tower-based fluxes into patch-wise contributions. Similar concepts were adopted to use a paired-tower experimental design (Matthes et al. 2014; Helbig et al. 2016; Griebel, Metzen, Boer, et al. 2020), leveraging spatially disjoint or partially overlapping flux measurements to separate flux contributions. In rare cases, a single flux tower was strategically placed at the boundary between distinct land-cover or land-use parcels to achieve spatial sampling goals (Fenster et al. 2023; Buzacott et al. 2024). These examples underscore the importance of incorporating additional spatial information to refine the decomposition of tower-based fluxes into their component contributions. However, caution should be exercised, as each introduced spatial information has its own assumptions and uncertainties, ultimately propagating into the spatial flux products.

Most approaches involved specific core models to disentangle spatial variability from temporal dynamics driven by other confounding factors (e.g., climate, soil, phenology). Yet, the types, structures, and complexity of models spanned a broad spectrum. Several studies have employed statistical models, including multiple linear models, general additive models, and hierarchical models (Matthes et al. 2014; Xu, Wang, et al. 2017; Tuovinen et al. 2019; Levy et al. 2020; Fenster et al. 2023; Romero et al. 2026). A few adopted simple biophysical models that have been widely used to interpret or fill gaps in CO_2 or CH_4 fluxes (Wang et al. 2006; Duman and Schäfer 2018; Tikkasalo et al. 2025). While varying slightly in model structures, these studies began with predefined functional types (i.e., categorical spatial effects) within the footprints and separated spatial effects from the temporal covariates, such as radiation and temperature. On the other hand, several studies have treated spatial effects as continuous and incorporated specific remote-sensing surface characteristics as model inputs (e.g., spatial covariates), including simple process-based models (Ran et al. 2016), machine learning (Xu, Metzger, and Desai 2017; Metzger 2018; Pirk et al. 2024), or a hybrid of both (Wiesner et al. 2022). These examples reiterate the importance of incorporating spatial dynamics into the modeling framework. To some extent, the choice of models depends on how flux sources and sinks vary spatially across sites and how models can discern that spatial variability from the often prevalent temporal dynamics.

While each is promising individually, there have been few attempts to benchmark the proposed approaches and apply them extensively across sites. We attribute the research latency to the following challenges. First, several of the proposed approaches began with pre-identified and hypothesized spatial compositions, gradients, or hotspots, which largely influenced model choices and the complexity of subsequent processes. Systematically obtaining and generating such "spatial priors" can be challenging to scale up and standardize across hundreds or thousands of sites. In particular, CH_4 and N_2O hotspots can form driven by belowground biogeochemical and microbial processes, which are challenging to detect using remote sensing. Second, a few approaches used continuous spatial forcings (e.g., the Enhanced Vegetation Index [EVI] and Land Surface Temperature [LST]), which showed promising results for delineating spatial flux gradients at finer spatial resolutions. Yet, as discussed in earlier sections, data limitations arise because there is currently no single remote-sensing product that fully resolves the spatial, temporal, and spectral scales of flux dynamics. Third, most previous approaches require specific core models to capture and ultimately separate the spatial and temporal flux dynamics. Most of these attempts relied on prior knowledge of the flux-controlling mechanisms, which are likely to vary across sites in different biomes and climates, or even within fine-scale patches within a site, further complicating the generalization of approaches across sites. Moving forward, we urge the flux community to tackle these challenges by benchmarking multiple approaches across sites and, in particular, showcasing best practices and their applicability to many research and real-world applications discussed in all previous sections.

4.4 | An Integrated Nesting Paradigm

One ultimate goal of the global flux networks and the thousands of eddy-covariance towers that constitute them is to provide flux information everywhere, all the time (D. D. Baldocchi 2008). A central challenge is how to bridge local, footprint-wise flux data with various observations and models across spatial and temporal scales to support environmental change assessments at regional or global scales. To some extent, the multiple approaches discussed in this article reflect the complexity of the challenge and suggest that there may not be a universal solution. A recent workshop on "Remote Sensing and Fluxes Upscaling for Real-world Impact," with over 100 participants from experimentalists, modelers, and practitioners, proposed a nesting paradigm to tackle this multi-scale, cross-disciplinary challenge (Figure 4) (Falco et al. 2024). The nesting paradigm particularly highlighted the strategic and implementation importance of "Straight Shot Scaling" and "Explicit Nesting" within the upscaling framework. The former refers to the typical upscaling framework adopted by many previous process-based or data-driven modeling studies (Sections 3.2 and 4.2), in which models are trained and parameterized at local, footprint-wise scales and then extrapolated to regional and global scales. The latter refers to methods that resolve spatial footprint dynamics at local scales, attribute flux contributions, and integrate them

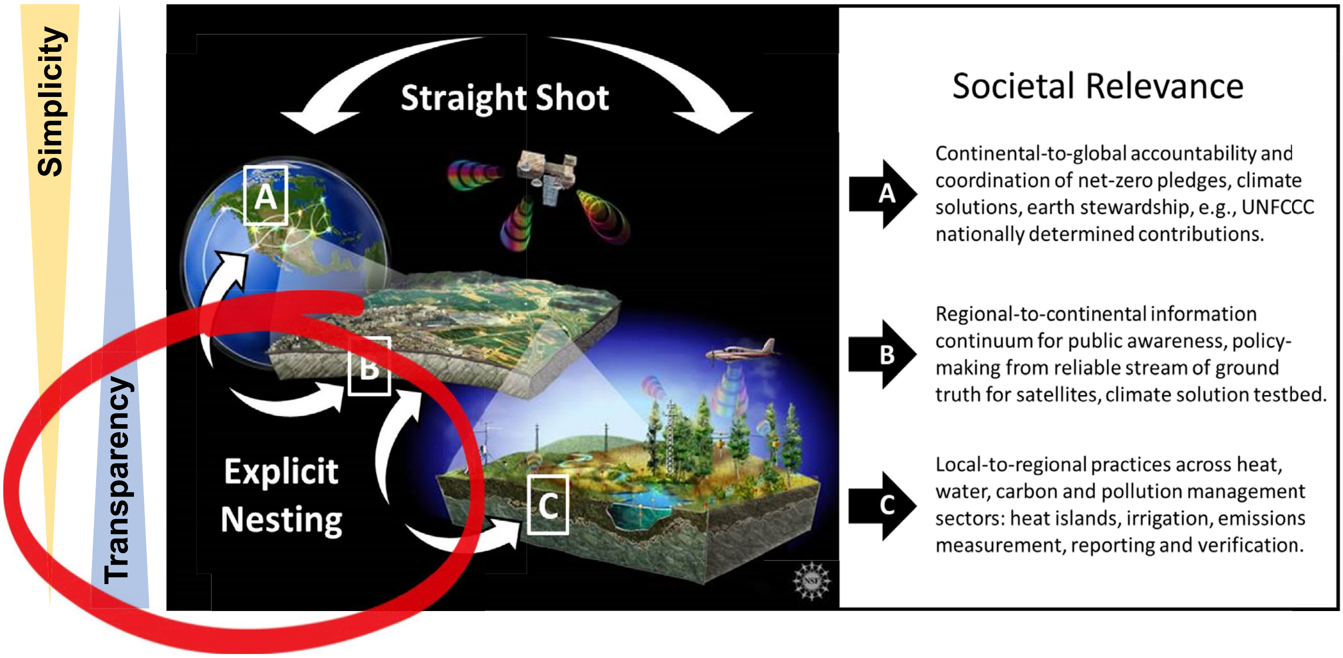

FIGURE 4 | The nesting paradigm for upscaling fluxes, illustrated as an "information conveyor belt" from flux tower footprints to regional maps and ultimately to global models and decision-making frameworks. The figure is adapted from the Remote Sensing and Fluxes Upscaling for Real-World Impact Workshop Report (Falco et al. 2024), based on the graphic created by NEON (2008).

into the landscape scales (Section 4.3). The two approaches complement each other in terms of feasibility and scalability, enabling them to meet societal needs at relevant scales. In the meantime, they also challenge each other through their divergent assumptions about preserving scale-wise and emergent behaviors, thereby providing stronger constraints to ensure the transparency, consistency, and interpretability of the upscaled fluxes.

5 | Closing Remarks and Outlook

The various attempts to address footprint dynamics highlight the importance of revisiting how we interpret and treat eddy-covariance flux data across applications. Essentially, flux data should be regarded as spatiotemporally dynamic rather than purely time-series data. This missing spatial aspect could complicate how we process eddy-covariance fluxes, define the mass and energy continuity, and interpret the flux response functions and parameters, all of which pose significant implications in numerous applications and research, such as those for accounting carbon, water, and energy budgets, benchmarking flux data with all sorts of observations and models, and informing resource management and policymaking. We urge the community to further investigate and evaluate potential approaches to bridge this knowledge gap across scales, disciplines, and applications, notably to support large-scale synthesis, data-model integration, and upscaling initiatives based on global network flux datasets.

Author Contributions

Housen Chu: conceptualization, methodology, resources, visualization, writing – original draft, writing – review and editing. **Stefan Metzger:** conceptualization, visualization, writing – original draft, writing – review and editing. **Zutao Ouyang:** writing – original draft, writing – review and editing. **Anne Griebel:** writing – original draft, writing – review and editing. **Koong Yi:** writing – original draft, writing – review and editing. **David Durden:** visualization, writing – original draft, writing – review and editing. **Sebastian Wolf:** writing – original draft, writing – review and editing. **Kuno Kasak:** writing – original draft, writing – review and editing. **Camilo Rey-Sanchez:** writing – original draft, writing – review and editing. **Leila Constanza Hernandez Rodriguez:** writing – original draft, writing – review and editing. **Patty Oikawa:** writing – original draft, writing – review and editing. **Nicola Falco:** writing – original draft, writing – review and editing. **Benjamin R. K. Runkle:** writing – original draft, writing – review and editing. **Arman Ahmadi:** writing – original draft, writing – review and editing. **Jaclyn Matthes:** writing – original draft, writing – review and editing.

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

This review is based on published literature. No original data were used.

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