

Review

Using Horizontal LiDAR Scans to Capture Net CO₂ Emissions at Intra-Urban Spatial Granularity: A Review

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Abstract

Urban areas contribute a dominant share of global carbon dioxide (CO₂) emissions, yet city-scale emission estimates remain highly uncertain due to the limited spatial and temporal resolution of existing observation methods. This review paper examined the potential of horizontally scanning Differential Absorption LiDAR (DIAL) systems to address these gaps in urban CO₂ monitoring. We reviewed current top-down and bottom-up approaches, identified their limitations in resolving intra-urban variability, and outlined a conceptual framework for deploying compact, eye-safe CO₂ DIAL systems on elevated urban structures. We reviewed methods that combined horizontal CO₂ scanning with wind measurements to enable high-resolution mapping of CO₂ distributions, assessment of boundary-layer effects, and estimation of urban carbon fluxes using established mass-balance and inversion techniques. Conceptual deployment scenarios, illustrated using Boston as an example, demonstrated how a single elevated LiDAR unit could provide near-city-wide coverage and capture neighborhood-scale emission patterns. We further discussed calibration strategies, safety considerations, and integration with existing sensor networks and column observations. This review concluded horizontal CO₂ LiDAR represents a promising pathway toward high-resolution, observation-based urban carbon monitoring, offering a complementary tool to existing methods and supporting future efforts to verify emission inventories, evaluate mitigation policies, and advance city-scale carbon management.

Keywords: urban CO₂; horizontal LiDAR; DIAL; carbon emissions; urban fluxes

1. Introduction

Carbon dioxide (CO₂) is a colorless, odorless gas at atmospheric pressure and temperature, and it is mostly non-reactive. It is one of the major greenhouse gases globally and studies have shown that cities exhibit higher CO₂ levels compared to the surrounding rural areas; this is also referred as an urban CO₂ dome [1,2]. Urban areas contribute over 70% of global CO₂ emissions, yet the intra-urban emissions remain poorly understood.

Over the past decades, global initiatives such as the Kyoto Protocol [3] and the Paris Agreement, 2015 have been established to guide the reduction and management of anthropogenic CO₂ emissions. To understand the effectiveness of climate change policies and regulations, it is necessary to monitor and observe CO₂ at high spatial and temporal resolution. The error in carbon emission (metric tonnes of carbon dioxide equivalent (CO_{2e}))



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is estimated to be around 6–10% at the global scale, but the uncertainty for urban areas remains significantly larger/unknown, with estimates ranging from 50 to 100% [4,5]. This contrast highlights that while global emissions estimates are relatively well-quantified, city-level emission estimates remain highly uncertain. This can be attributed to the lack of data availability at high spatio-temporal resolution within cities [6]. Additionally, factors such as local emissions, wind speed, vertical mixing, and microclimate significantly influence urban CO₂ levels, which can further lead to errors in emission estimations.

Understanding the distribution of carbon dioxide in cities is essential for developing effective carbon emission mitigation strategies [7]. Most cities rely largely on bottom-up inventories that aggregate activity data from transportation, industry, fuel consumption, and land use [8,9]. These inventories are indispensable for policy and planning because they describe sector-specific emissions. However, they are often limited in their spatial and temporal resolution [7]. Inventories can also become outdated quickly as urban landscapes, population behavior, and energy systems evolve. For this reason, independent verification through atmospheric measurements is critical.

Another approach involves top-down methods that infer emissions from observed atmospheric CO₂ concentrations [10–12]. The emissions are then estimated using inverse modeling, which converts the CO₂ concentration measurements into emissions [13,14]. These methods rely on atmospheric transport models and a combination of CO₂ measurements from satellite observations, aircraft campaigns, flux towers, and in situ sensors. Satellite platforms such as GOSAT (Greenhouse Gases Observing Satellite) and OCO-2 (Orbiting Carbon Observatory-2) provide essential information on global carbon dioxide distribution [15]. Still, their spatial resolution and temporal sampling are not well-suited to resolve the fine-scale variability in cities. Aircraft campaigns and tall-tower measurements offer more precision, but they are logistically intensive and typically limited in both coverage and duration. Flux towers offer vertical profiles that can provide accurate carbon flux measurements, but are generally located outside urban centers and do not function very well with the complex and multiple sources in urban environments [16].

There is a growing recognition that high-resolution observations are needed to capture the true spatial and temporal dynamics of carbon dioxide across the urban landscape [17]. The ability to observe these patterns directly would allow researchers and policy-makers to verify emissions inventories, evaluate mitigation efforts, identify unexpected sources or sinks, and detect the influence of microclimatic processes [18]. Several cities have begun to deploy low-cost sensor networks for this purpose [19,20]; one example is the BEACON (BERkeley Atmospheric CO₂ Observation Network) [21]. However, despite their significant improvement over other techniques, such networks still lack the vertical and horizontal coverage required to capture the spatial heterogeneity of emissions in complex urban settings. The network of such large sensors is also difficult to manage and calibrate, and reliable sensors can typically cost ~\$4000 per sensor node [22]. This can lead to high costs for a network of high spatial resolution coverage in urban areas and would further require significant efforts and costs to maintain.

In this context, LiDAR (Light Detection And Ranging) technology offers a unique opportunity. LiDAR uses laser pulses to measure atmospheric properties along the path of the beam [23]. Differential Absorption LiDAR, or DIAL, is particularly powerful because it can directly measure gas concentrations by comparing absorption at two nearby wavelengths, one that is absorbed by the target gas and one that is not [24]. A LiDAR system that performs horizontal scanning at the height of the urban boundary layer could provide continuous, spatially distributed measurements of particulate matter or gases across an entire city, as shown previously [25]. By scanning at regular intervals, the system could reveal the evolution of carbon dioxide patterns in response to daily cycles, meteorological

changes, or human activity. CO₂ remote sensing via DIAL has a well-developed literature in geological and volcanic applications, covering the same wavelengths and detection approaches used in urban deployments [26]. The absence of an equivalent review for urban applications is one of the motivations for the present paper.

Study Objectives and Scope of the Review

The main objective of this review is to explore the potential application of a horizontal scanning LiDAR system in cities for obtaining high spatial and temporal resolution of CO₂ distribution. This review serves as a roadmap for researchers interested in applying horizontal scanning LiDAR in urban settings. This paper achieves the following:

- Discusses the implications of designing and deploying LiDAR systems capable of measuring urban CO₂ concentrations;
- Describes the types of information that can be retrieved using current LiDAR systems;
- Outlines example deployment strategies using the city of Boston, USA;
- Reviews different installation configurations and calibration approaches for LiDAR-based CO₂ data.

In addition, we review existing LiDAR technologies and summarize their current limitations, emphasizing the need for further technological development to enable detailed mapping of urban CO₂ distribution. By synthesizing these elements, this review provides guidance for the use of horizontally scanning LiDAR systems in urban CO₂ monitoring at high spatial and temporal granularity, supporting efforts to detect carbon sources and sinks across cities and to stimulate discussion, collaboration, and innovation among researchers and urban stakeholders. This review is positioned as a focused conceptual roadmap for deploying LiDAR system in urban areas for CO₂ sensing rather than an exhaustive survey of all technologies. Its specific contribution is the identification of horizontally scanning DIAL as an underexplored paradigm for intra-urban monitoring, and the provision of a concrete deployment and flux-estimation framework grounded in current hardware capabilities.

Further, this review is organized around a single analytical question: does a monitoring gap exist in urban CO₂ measurement at the neighborhood scale, and can horizontal scanning DIAL fill it? We define this gap as the spatial–temporal range of 100 m to 10 km and 15 min to 1 h, the scale at which individual city districts, traffic corridors, and land-use zones produce distinct and detectable CO₂ signals, but at which no currently available measurement system can provide continuous, direct flux estimates. We show that this gap is real by examining the capabilities of existing methods (Section 2) and demonstrating that horizontal scanning DIAL is the only currently demonstrated measurement approach that can potentially fill it (Section 3). Sections 4 and 5 then assess whether the specific applications motivating the review—policy verification, biogenic sink detection, inventory validation, and intra-urban flux mapping—are achievable with the demonstrated and projected performance of the technology. Section 6 identifies technical gaps and limitations.

2. Method

The literature cited in this review falls into two categories. The first is the LiDAR and DIAL technology literature, which forms the core of the review. This was identified through a targeted Web of Science search using three queries: (1) ‘differential absorption LiDAR’ AND ‘CO₂’, returning 50 records; (2) ‘DIAL’ AND ‘CO₂’ AND ‘urban’, returning 17 records; and (3) ‘horizontal scanning’ AND ‘LiDAR’ AND ‘CO₂’, returning 14 records. This search resulted in 78 unique records in total after removing duplicates. A parallel Google Scholar search was conducted with the same keywords. In the original manuscript, 10 LiDAR/DIAL-specific papers were cited; the revision adds 16 more identified from these exports and citation tracking, giving 26 LiDAR/DIAL-specific references in total. The

second category is contextual background references, covering urban CO₂ observations, emission inventories, greenhouse gas policy, flux methods, satellite observations, and low-cost sensor networks. These 39 references were identified through standard reading during writing and are not from the LiDAR-specific search. Altogether, the manuscript cites 65 references. Within the LiDAR/DIAL literature specifically, publication volume on ground-based 1.57 μm CO₂ DIAL systems has grown substantially since 2015, coinciding with the maturation of SNSPD technology and commercial fiber-laser amplifiers at this wavelength. Geographically, approximately 14 of the 26 LiDAR-specific references are from China, with the remainder from the USA, Europe, and Japan, reflecting the high investment in SNSPD fabrication and 1.57 μm fiber-laser development in China over the past decade.

The screening process was performed in three stages for DIAL and LiDAR: (1) title screening to remove clearly irrelevant studies, (2) abstract screening to assess relevance to atmospheric gas sensing and urban applications, and (3) full-text review for methodological and technical relevance. Studies were included if they met at least one of the following criteria: (i) reported LiDAR-based measurements of CO₂ or related atmospheric gases, (ii) demonstrated horizontal or scanning-based LiDAR configurations, (iii) addressed urban or near-urban deployment contexts, or (iv) contributed to flux estimation, inverse modeling, or integration with wind measurements. Foundational studies on top-down and bottom-up carbon monitoring approaches were also included to provide context. Studies were excluded if they focused solely on non-atmospheric LiDAR applications (e.g., topographic mapping), lacked gas-sensing capability, or did not contribute to urban-scale monitoring frameworks.

For each selected study, key information was extracted, including system configuration, sensing principles, spatial and temporal resolution, deployment strategy, and reported limitations. The findings were synthesized qualitatively to identify technological trends, methodological gaps, and opportunities for future development of urban CO₂ LiDAR systems.

3. CO₂ LiDAR System: Technical Design

Differential Absorption LiDAR (DIAL) operates by emitting laser pulses at two closely spaced wavelengths, one tuned to a CO₂ absorption line (“on-line”) and one off that line (“off-line”), measuring the difference in the returned backscatter signals. Because CO₂ molecules absorb the on-line wavelength, the attenuation of the returned (backscatter) signal can be used to derive the path-integrated CO₂ amount. With a pulsed laser and time-of-flight ranging, this technique yields the CO₂ concentration at different distances (ranges) along the laser path. In essence, DIAL provides a direct, range-resolved measurement of the CO₂ distribution in the atmosphere, effectively “dialing in” to CO₂ molecules specifically. This specificity and range resolution is much higher than the traditional methods. Unlike a stationary point sampler or a satellite column average, a DIAL can capture actual concentration gradients in the air, revealing fine-scale structures such as plumes and pockets of clean air that were previously blurred out in coarse measurements. An early coherent 2 μm DIAL and wind LiDAR demonstrated range-resolved CO₂ and wind measurements with 150 m spatial resolution [27]. Despite operating at 2 μm , this system established the dual-channel coherent DIAL architecture that was later refined at 1.57 μm . One of the first ground-based demonstrations of a 1.57 μm DIAL transmitter using direct (non-coherent) detection achieved 1–2 ppm precision at 1–2 km range [28]. This work established the measurement concept that later instruments extended to longer ranges and higher sensitivity using coherent detection and SNSPD arrays.

To implement horizontal CO₂ LiDAR monitoring in a city, we outline a DIAL-based system architecture with an emphasis on mobility, safety, and integration. The core of the

system is a 1.57 μm pulsed DIAL transmitter. The on-line wavelength is tuned to a specific CO_2 absorption feature in the near-IR, and an off-line wavelength (just a few nanometers away) serves as the reference. These paired laser pulses (on-line/off-line) are emitted alternately at a high repetition rate. In a typical configuration, the laser beam is transmitted into the atmosphere and the backscattered signal is collected by a receiver-side telescope. The receiver uses a sensitive detector (such as an avalanche photodiode or an SNSPD array) to record the time-resolved backscatter signal for each pulse. By comparing the return signals of on-line vs. off-line pulses, the system computes the CO_2 concentration at different ranges along the beam. Single-photon-sensitive detectors, especially superconducting nanowire single-photon detectors (SNSPDs), have significantly improved the signal-to-noise ratio of DIAL measurements [29]. By counting individual photon returns with low noise, these detectors enable the DIAL system to detect tiny fluctuations in CO_2 at meter-scale resolution. For instance, researchers in Sweden demonstrated a continuous-wave DIAL system using a fiber laser and SNSPD that could resolve CO_2 concentration changes over a 2 km test path in an urban setting [30]. This compact, low-power setup was able to sensitively track CO_2 variations (even overnight when the CO_2 concentration variability is very low), proving that high-resolution urban CO_2 monitoring is achievable using compact LiDAR units. In general, the DIAL concept allows us to perform horizontal scans across the urban atmosphere, by steering the laser beam in different directions, thereby mapping how CO_2 is distributed across a city. This horizontal scanning LiDAR framework forms the basis for new observation strategies to understand CO_2 sources and sinks in the urban environment.

As illustrated in Figure 1, recent implementations have demonstrated a compact hybrid LiDAR architecture that integrates a CO_2 DIAL channel with a coherent Doppler wind LiDAR (CDWL) channel within a single system [31]. In this design, both subsystems share a common 1.57 μm fiber-laser transmitter, optical collimator, and control electronics, while employing separate receiver chains optimized for gas concentration and wind-field measurements. The on-line and off-line wavelengths are alternated at kilohertz rates using a fast optical switch and an acousto-optic modulator, ensuring identical pulse shapes prior to amplification by an erbium-doped fiber amplifier. Atmospheric backscatter is collected by dual telescopes and routed either to a balanced heterodyne detector for CDWL-based wind retrieval or to a multimode-fiber-coupled, filtered DIAL receiver employing a superconducting nanowire single-photon detector (SNSPD) for CO_2 sensing. This hybrid configuration enables simultaneous retrieval of CO_2 concentration and wind information over kilometer-scale ranges, highlighting how integrated DIAL–CDWL systems can support horizontally scanning, high-resolution urban carbon monitoring [31]. Airborne pulsed DIAL at this wavelength has achieved column CO_2 retrievals with precision better than 1 ppm over a wide range of surface types [32], confirming the spectral line parameters and atmospheric transmission characteristics needed for ground-based urban deployment. Ground-based coherent DIAL has been shown to measure CO_2 mixing ratios in the lower troposphere with precision below 1 ppm under clear-sky conditions by using cloud boundaries as hard targets [33], demonstrating that ppm-level precision is achievable without artificial retroreflectors.

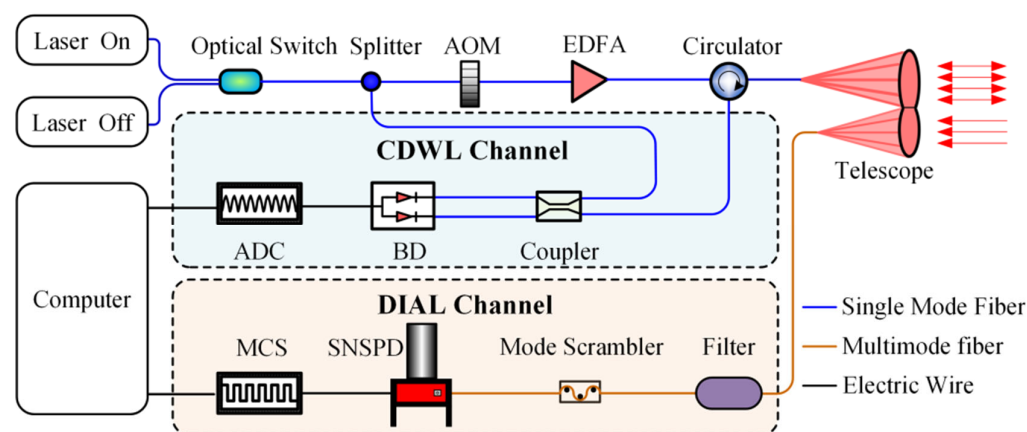


Figure 1. Proposed low-cost and compact LiDAR design and components (source: adapted from [31]). Note: Reproduced from [31], [Remote Sensing]; published by [MDPI], 2022, creative common license 4.0. The schematic illustrates: the shared 1.57 μm fiber-laser/CPA transmitter; the acousto-optic modulator (AOM) that switches rapidly between online and offline wavelengths on alternate pulses; the dual-channel receiver separating the DIAL signal (for CO_2 retrieval) for ppm-level CO_2 measurement at 6+ km range. The DIAL system operates at ~ 2.7 K and requires a closed-cycle cryo-cooler.

Taken together, the reviewed DIAL systems show a consistent technical trajectory. Range performance has improved from 1 to 2 km (early 2010s, direct detection [28]) to 6–7 km (post-2020, coherent detection with SNSPD), driven primarily by detector advances rather than laser power increases. All systems that achieve ppm-level sensitivity at these ranges use SNSPD arrays [31,34], pointing to detector efficiency as the critical limiting factor and to SNSPD operational cost as the main barrier to routine deployment. The shift from vertical profiling to horizontal sector scanning, demonstrated by Yue et al. [31] and extended to 3D by Yu et al. [34], represents a fundamental change in measurement philosophy: instead of profiling the atmosphere above a single point, horizontal scanning samples a cross-section of the urban boundary layer that integrates emissions from an entire sector of the city. However, a critical validation gap remains. While DIAL CO_2 concentration retrievals have been independently validated against aircraft [32], satellites [35], and in situ analyzers [33,36] in multiple campaigns, the horizontal flux estimates derived from DIAL scans have been validated in only one urban deployment [31] and one volcanic deployment [37]. Expanding this flux validation across different cities, seasons, and meteorological conditions is the most urgent experimental need in the field. The most recent results in the field extend the state-of-the-art in two directions. First, Yu et al. [34] demonstrated simultaneous 3D CO_2 and wind retrieval with a coherent 1.57 μm DIAL transmitter, going beyond the 2D sector scans of the Nanjing prototype [31] to full volumetric coverage. Second, Cao et al. [38] quantified the Doppler-shift bias introduced by atmospheric wind into the CO_2 retrieval: at typical urban wind speeds of 3–10 m/s, the uncorrected bias reaches 1–3 ppm, comparable in magnitude to the CO_2 signal being measured. The dual-channel DIAL + Doppler architecture used in [31] was specifically designed to measure and correct this bias simultaneously. Together these results establish the current performance frontier: ppm-level CO_2 with simultaneous 3D wind, at 6–7 km range, in a real urban environment.

3.1. Deployment and Mounting

CO_2 concentrations can change significantly with height due to shifting planetary boundary layer (PBL) height. These variations are not random but follow predictable meteorological cycles that influence how anthropogenic emissions and biogenic fluxes are expressed in the atmosphere. PBL height shows diurnal as well as seasonal variation. PBL

height can range from as low as 50 m at night up to 2000 m during the day [39], as well as varying from season to season.

A study in Seoul used these boundary level height variations and showed that differences in CO₂ levels at different heights can reveal how the planetary boundary layer (PBL) traps urban emissions at night and can help distinguish between anthropogenic and natural carbon emissions [40]. Importantly, a shrinking nighttime PBL does not selectively trap anthropogenic CO₂; rather, it limits vertical mixing for all near-surface sources. However, because urban anthropogenic emissions are typically continuous, spatially concentrated, and dominated by combustion sources, their signals become more pronounced under shallow nighttime PBL conditions, while many biogenic fluxes are reduced or change sign during the night.

Under stable nighttime conditions, emissions from cities tend to accumulate near the surface, making it possible to distinguish urban CO₂ signals from regional background concentrations influenced by natural sources or long-range transport. This separation is important for estimating the contribution of cities to overall CO₂ emissions. In contrast, during daytime conditions, the planetary boundary layer is generally well-mixed, which reduces the contrast between local and regional CO₂ signals.

Simply put, the boundary layer acts like an invisible lid that rises and falls through the day, controlling how carbon dioxide and other gases/pollutants spread vertically. Deploying a horizontally scanning CO₂ LiDAR at elevations of approximately 200–300 m above ground allows for observations across this evolving boundary layer, capturing how urban CO₂ accumulates under shallow nighttime conditions and becomes more vertically dispersed during the day. From an elevated LiDAR platform, these changes in CO₂ distributions associated with nighttime stratification and daytime mixing can be directly observed, enabling the separation of city-scale CO₂ signals from more vertically uniform regional background concentrations, as illustrated schematically in Figure 2. This information can inform the design, monitoring, and evaluation of city-level carbon management strategies. In Figure 2, red arrows indicate carbon emission sources, while green arrows represent carbon sinks. Urban trees function primarily as carbon sinks during the daytime due to photosynthetic uptake but can act as net carbon sources at night because of respiration. Water bodies may behave either as carbon sources or sinks, depending on local biogeochemical and atmospheric conditions, as illustrated in Figure 2. In contrast, residential and commercial areas are depicted as persistent carbon sources associated with anthropogenic activities.

Having the scanning LiDAR system on an elevated vantage point within the city maximizes its coverage area. Mounting the instrument on a tall building (approximately 100–300 m above ground level) provides a wide, unobstructed line-of-sight across surrounding neighborhoods. As demonstrated using Boston's 3D city model (Figure 3), a DIAL transmitter placed atop the Prudential Tower can achieve clear visibility (clear line of sight- denoted by green color) over almost the entire city, covering a radius of ~7 km with only one angular blind spot (denoted in red color). The line-of-sight coverage map in Figure 3 was computed using the City of Boston's 3D building model, available through the Analyze Boston open data portal (<https://data.boston.gov>, accessed on 21 January 2026). This dataset provides parcel-level building footprints and height measurements across the entire city. For each azimuthal direction from the Prudential Tower rooftop (~230 m AGL, 42.347 N, 71.081 W), a horizontal ray was projected at the instrument elevation. The first building in the dataset whose height exceeded the ray height was recorded as the obstruction for that bearing. Green sectors in Figure 3 show clear line-of-sight to 7 km; red sectors show where a building blocks the beam at a shorter range. The 7 km range corresponds to the maximum distance at which the 1.57 μ m DIAL transmitter achieves sufficient signal-to-noise ratio for 1–2 ppm CO₂ retrieval under typical urban aerosol loading.

This is extrapolated from the 6 km demonstrated in the literature [31], who used the same wavelength and similar detector configuration. Actual deployment parameters would need to be determined from site-specific SNR measurements and optimization of the scan protocol for the local atmospheric conditions. This height allows the beam to remain above most buildings and infrastructure, enabling effective sampling of the well-mixed urban boundary layer. A rotating scanning mechanism, such as a motorized platform on which the LiDAR system is mounted, then steers the laser beam azimuthally to perform full 360° horizontal scans. The LiDAR system then performs a plan-position indicator (PPI) scan, i.e., rotating 360° (or a chosen sector) at a fixed elevation angle to map concentrations across the city's horizon. The suggested averaging, based on the previous work [31], is set for 10 s, with 2° radial increments in scanning angle; thus, a total 360° scan takes ~ 1800 s (30 min).

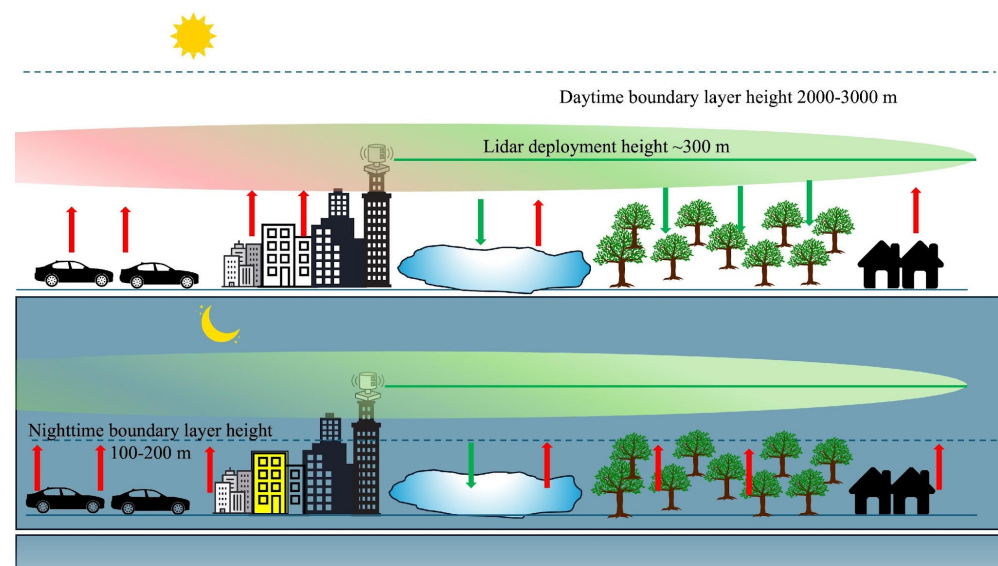


Figure 2. Conceptual side-view of elevated horizontal CO_2 scanning across changing boundary-layer heights in daytime and nighttime conditions. Note: Based on typical mid-latitude urban conditions. PBL height varies from ~ 50 to 200 m under stable nocturnal conditions to >1500 m during convective midday periods (an order-of-magnitude daily range), directly controlling the depth of atmosphere through which horizontal DIAL beams must be integrated for flux calculation. The CO_2 scanning layer is confined to the PBL. Green arrows indicate carbon sinks and red arrows indicate carbon emissions.

In our Boston case study scenario, one could imagine a DIAL system on the roof of the ~ 230 m Prudential Tower, scanning over the city at a slight downward tilt. The LiDAR beam could “slice” through the urban atmosphere above different neighborhoods such as downtown high-rises, residential areas, the Charles River, parks, etc., providing a panoramic CO_2 concentration map, as illustrated in the schematic Figure 4. The figure illustrates how a scanning DIAL system can map CO_2 across diverse urban zones. The city is depicted with various land-use areas, for example, a dense downtown, extensive residential neighborhoods, green parks, busy roadways/highways, and a river or waterfront. From these different zones, stylized plumes or color gradients indicate the relative CO_2 concentrations. Higher CO_2 “hotspots” are shown rising from major emission sources like heavy traffic on roads and city centers, whereas lower CO_2 levels appear over green and blue areas (parks and water) due to a lack of emissions and possible plant uptake. A range of 7–10 km radius would cover most of the city, and a spatial resolution of 10–20 m along the radial distance would provide significant information to understand the CO_2 distribution across the city.

horizontal wind speed and direction for each beam direction. Knowing the wind field is crucial for interpreting the transport of CO₂ plumes and for calculating fluxes (discussed later). The hybrid DIAL + Doppler approach has been demonstrated successfully in a recent prototype in Nanjing. The study combined these methods to simultaneously map CO₂ and wind across a 6 km range with ~150 m spatial resolution in ~15-s averaging for each scan [31]. More recently, Yu et al. demonstrated simultaneous 3D CO₂ and wind retrieval using a coherent 1.57 μ m DIAL transmitter over a horizontal scan volume, extending the Nanjing prototype concept from 2D sector scans to full 3D coverage [34]. The Doppler shift introduced by atmospheric wind at typical urban speeds (3–10 m/s) is sufficient to introduce a 1–3 ppm bias in the CO₂ retrieval if left uncorrected [38]. The dual-channel DIAL + Doppler architecture used in the Nanjing prototype [32] was specifically designed to measure and correct this bias simultaneously.

3.3. Technical Considerations for Safety

The LiDAR system proposed must be designed to remain eye-safe in an urban environment. The 1.57 μ m wavelength is relatively eye-safe (it lies in a spectral region where the human eye is less sensitive and radiation is largely absorbed by the cornea), and with proper beam divergence and power limits the system can be classified as Class 1 (eye-safe). We would ensure the beam is usually directed above the horizontal plane except during controlled calibration tasks, minimizing any direct exposure to people. The transmitter and optics would be housed in a weatherproof enclosure with a window transparent to 1.57 μ m. Since weather conditions can affect LiDAR performance, the system might pause or reduce operations during heavy rain or thick fog (which attenuates the infrared beam significantly). However, normal haze or light rain is typically manageable with adjustments to averaging time or power.

3.4. Calibration of the Raw LiDAR Data

Calibration and stability are important design aspects. CO₂ profiles measured with 1.6 μ m DIAL transmitter have been validated against aircraft in situ measurements, showing agreement to within 2 ppm up to 3 km altitude [35], providing independent confirmation that the retrieval algorithm is accurate at heights relevant to urban boundary layer scanning. The system can be periodically zero-calibrated by pointing at a reference cell or by pointing the LiDAR unit towards an EPA monitoring station and comparing the measured CO₂ levels from the reference monitors. Mounting on a tall building introduces challenges like platform motion (building sway in wind). To counter this, the LiDAR unit could use a gyroscopic stabilizer for the scanner or incorporate real-time pointing corrections (e.g., using feedback from a fixed target). Advances in fiber laser technology and robust optical components mean the entire DIAL unit can be made relatively compact, potentially a few tens of kilograms, allowing it to be mobile (for instance, mounted on a vehicle or easily relocated between rooftops) [41–43]. The experimental setup would involve initial test scans on a flat, open area to validate performance, followed by installation at the chosen urban site for continuous operation and calibration of the raw LiDAR data. Data from the LiDAR system would be streamed in real time to a processing unit that applies the DIAL equation to retrieve CO₂ concentrations every few meters along the beam, building up a 2D map of CO₂ for each scan rotation.

4. Applications of Horizontal Scanning LiDAR

4.1. Effectiveness of Emission Reduction Intervention Policies

A city-deployed CO₂ LiDAR system can offer insights for climate science research and policy-makers for urban planning and implementation of regulations. City gov-

ernments often implement interventions (like new traffic regulations, public transit improvements, tree-planting programs, or energy efficiency mandates) aimed at reducing emissions [44–47], but verifying their impact is challenging. If deployed and operated continuously, a CO₂ LiDAR system could in principle provide near-real-time feedback on such interventions, though this has not yet been demonstrated in a policy context. For instance, if a low-emission zone is established in a city center (restricting high-pollution vehicles) [47–49], the LiDAR system should detect a reduction in CO₂ concentrations over that area during enforcement hours, compared to pre-policy baselines. If a congestion pricing scheme is expected to cut traffic emissions by a certain percentage (as modeled in simulation studies), the LiDAR system could measure the actual drop in CO₂ over roads during peak hours, thus verifying (or refuting) the predicted gains. This kind of independent emissions verification is crucial for climate action plans, as it turns abstract policy goals into measurable atmospheric outcomes. This scenario requires the instrument to detect a change in net city-scale CO₂ emissions. To achieve this, the DIAL system must cover the full city boundary with sufficient azimuthal sampling to close the horizontal flux integral without large gaps. A full 360-degree rotating scan with 2-degree azimuthal steps at 7 km range, repeated every 30 min, provides the necessary spatial completeness. The horizontal flux divergence method (Section 5.1) is the appropriate flux estimation approach because it directly integrates the measured CO₂ flux across the full city boundary using the same scan geometry.

4.2. Biogenic Sources and Sinks Within the Cities

Furthermore, high-resolution CO₂ observations will improve our understanding of urban plume dynamics and the balance between carbon sources and sinks within cities. In particular, the contribution of water bodies and urban parks to biogenic CO₂ exchange remains uncertain because traditional monitoring systems lack the spatial and temporal resolution needed to capture their variability. A scanning LiDAR system can resolve these fine-scale patterns and clarify whether such features act as net sources or sinks of carbon. For instance, recent studies have shown that certain urban lakes and reservoirs may behave as substantial CO₂ emitters or sinks [50,51]. If high-resolution observations confirm that a given water body is a significant source, city authorities could diagnose the underlying drivers, such as eutrophication, and intervene to enhance carbon sequestration [50]. Ultimately, these measurements enable city officials and researchers to identify neighborhood-scale emission hotspots, track their dispersion, and make targeted decisions to manage and mitigate urban carbon emissions more effectively. Detecting the biogenic CO₂ signal requires resolving concentration differences between vegetated and built-up sectors of the scan, against the diurnal background variability. This is the most demanding scenario in terms of measurement precision. It requires range-resolved measurements at 150 m resolution or finer, with scan cycles repeated frequently enough (every 15–30 min) to track the diurnal pattern of photosynthesis and respiration. The atmospheric inversion method (Section 5.3) is most appropriate here, as it can decompose the spatial distribution of measured CO₂ into contributions from distinct sources and sinks, including vegetation patches within the city.

4.3. Validate Emission Inventories

The LiDAR data can also be used to validate and improve emission inventories at fine scales. Cities compile CO₂ inventories down to sectors or districts, but these are based on calculations and assumptions [52]. Six different atmospheric transport models tested against aircraft observations of power plant CO₂ plumes all showed significant errors in plume shape and magnitude, with even the best-performing model deviating from

observations by 20–40% in peak concentration [53]. This demonstrates that model-based inventory validation cannot substitute for direct atmospheric measurement. By comparing the observed concentration enhancements in the atmosphere with inventory predictions (through atmospheric modeling), one can identify which parts of the inventory are accurate and which might be under- or over-estimated [54]. For example, if the inventory assumes a certain industrial area emits X tons of CO_2 per day, the LiDAR unit's measured concentration plume downwind of that area (combined with wind data) can be cross-checked against X . If the measured signal is consistently stronger, it may indicate actual emissions are higher than reported (or vice versa). In one demonstration, a scanning DIAL system in Nanjing was able to distinguish an industrial zone that was a net CO_2 source from a nearby university campus and park area that were roughly CO_2 -neutral in net flux [31]. It has been shown that even large industrial CO_2 point sources, which produce the strongest and most detectable signals, carry spaceborne LiDAR flux uncertainties of 10–20% [55]. This sets a practical accuracy benchmark: a ground-based horizontal DIAL measuring much closer to the source should be able to achieve significantly better accuracy. Such information directly flags which neighborhoods are major contributors and which are relatively balanced, guiding where mitigation or offsets might be most needed. Attributing measured CO_2 to a specific source, such as a power plant, a highway corridor, or an industrial district, requires the DIAL scan to isolate the plume downwind of that source. This means fixing the azimuth toward the source and scanning the elevation to build a cross-sectional plume curtain or using a sector scan that captures the plume at multiple angles. The vertical plume method (Section 5.2) is most appropriate because it integrates the CO_2 concentration directly across the curtain perpendicular to the wind, giving a direct flux measurement that does not require any dispersion model assumptions.

4.4. Urban Carbon Cycle

Another important implication lies in advancing our understanding of urban carbon cycling. The elevated CO_2 levels observed in cities, compared to surrounding rural areas, are often referred to as an urban CO_2 dome [1,2]. However, this dome may not be a single uniform feature. Instead, it may consist of several smaller domes and sinks within the city, driven by spatially variable sources and uptake of CO_2 . A mobile scanning DIAL unit deployed across different urban land-use types measured the CO_2 rectifier effect, the difference between daytime photosynthetic uptake and nighttime respiration enhancement, and found that it varies by 3–8 ppm depending on vegetation density even within a single city [56]. A fixed horizontal DIAL transmitter at rooftop height could resolve this spatial pattern continuously. High-resolution LiDAR measurements will allow researchers to study phenomena like the urban CO_2 dome's structure, boundary layer dynamics, and biogenic effects. For example, the system could capture the morning transition when the nocturnal boundary layer breaks up: just after sunrise, plants in urban green spaces begin photosynthesis and the boundary layer starts to grow, often leading to a temporary drop in near-surface CO_2 as the night's accumulation disperses. For example, for our case study scenario, a scanning DIAL unit on the Prudential Tower in Boston could continuously monitor the city's CO_2 "heartbeat." As morning rush hour begins, the LiDAR map might show narrow plumes of high CO_2 emerging along major highways like I-90 and I-93, corresponding to traffic emissions. Over downtown and commercial areas, the concentrations could start rising as heating systems and traffic activity ramp up. Meanwhile, the LiDAR unit might reveal that areas above the Charles River or large parks (Boston Common, the Emerald Necklace) have noticeably lower CO_2 levels during the day, as these open or green areas lack combustion sources and vegetation is actively taking up CO_2 . Such fine-grained observation was virtually impossible with earlier methods such

as using satellite data, flux towers, or sensor networks. With LiDAR, urban planners can identify hotspots (zones of consistently high CO₂) as well as CO₂ havens (localized clean air zones or net sinks) within the city. Mapping neighborhood-scale CO₂ cycle requires the full 360-degree scan combined with high azimuthal resolution (~2-degree steps). Unlike the policy verification scenario, where the total city flux is the target, here the spatial distribution of fluxes within the city is the target. The atmospheric inversion method (Section 5.3) is most appropriate because it is the only method that can spatially disaggregate the measured boundary concentration into contributions from multiple distributed sources within the scan domain.

4.5. Complementing Other Methods

Finally, while LiDAR provides spatial mapping, it can be complemented by other instruments for a more complete picture. LiDAR-observed data can be integrated with ground-based networks such as BEACON and Purple Air to understand CO₂ plumes and their dispersion. Another potential implication could be the use of Pandora-like spectrometers. For instance, we can deploy such instruments to operate one at the LiDAR site to obtain column-averaged CO₂ (or related gas) measurements overhead [57]. Although Pandora currently lacks the spatial resolution and capability to measure CO₂ in its standard configuration, the instrument can be redesigned to observe and retrieve CO₂ data. Its day-time total column measurements can provide an independent constraint on the calibration of the LiDAR system because the integrated LiDAR profile can be compared against what a direct-sun measurement observes. Integrating these datasets can improve overall accuracy and help relate fine-scale horizontal variations in CO₂ to broader-scale atmospheric changes. For example, local enhancements detected by the scanning LiDAR unit can be linked to simultaneous variations in total column CO₂ observed by Pandora or by satellites. Spaceborne LiDAR has been shown to be technically feasible for urban-scale column measurements, but the 1–3 km footprint of current satellite designs is too coarse to resolve intra-urban gradients [58]. A rooftop horizontal DIAL unit at higher resolution could serve as a surface-truth reference for such satellite missions. A planned atmospheric environment monitoring satellite will carry both CO₂ DIAL and wind measurement channels [59]. A ground-based horizontal DIAL network would provide the surface-level validation data that such a satellite mission cannot collect from orbit. In this way, the horizontal CO₂ LiDAR unit can function as a central component of an urban greenhouse gas monitoring system, supporting applications ranging from real-time pollution surveillance to evaluation of climate mitigation strategies.

5. Flux and Emission Calculations

The application scenarios described in Section 4 each impose different requirements on the flux estimation method. Policy verification (Section 4.1) uses the horizontal flux divergence method because it covers the full city boundary. Biogenic sink detection (Section 4.2) and urban carbon cycling (Section 4.4) both use the atmospheric inversion because they require spatial decomposition of distributed sources and sinks. Inventory validation for point sources (Section 4.3) uses the vertical plume method because it attributes flux to a specific known source without needing to model transport across the full domain. The three methods described below are essential for different tasks, and an operational horizontal DIAL system would use all three depending on the study objective. For the successful deployment of the proposed scanning LiDAR system and its implications, it is essential to rigorously analyze the measurements to derive reliable fluxes and emission estimates. A scanning CO₂ differential absorption LiDAR (DIAL) system combined with wind measurements can be used to directly estimate carbon fluxes in and out of different

parts of a city. By mapping CO₂ concentration in the atmosphere and simultaneously measuring wind, one can calculate how much CO₂ is flowing through a given area, essentially translating atmospheric observations into emissions or uptake rates. Several modes have been demonstrated in research for deriving fluxes from CO₂ concentration data, each with underlying equations grounded in atmospheric transport principles. We summarize three key approaches below, with formulas from the literature and how they can be integrated with the CO₂ concentrations obtained from LiDAR data. Before converting DIAL-measured mixing ratios to fluxes, the CO₂ molar number density n_{CO_2} (mol m⁻³) must be calculated as $n_{\text{CO}_2} = \chi \times P / (R \times T)$, where χ is the volume mixing ratio (mol mol⁻¹, equal to ppm $\times 10^{-6}$), P is atmospheric pressure (Pa), T is air temperature (K), and $R = 8.314 \text{ J mol}^{-1} \text{ K}^{-1}$. Mass concentration (kg m⁻³) is then obtained by multiplying by the molar mass of CO₂ (0.04401 kg mol⁻¹). Simultaneous measurements of P and T along the beam path, from co-located meteorological sensors or assimilated weather model fields, are required for this conversion. The three flux estimation methods described below each also rely on specific atmospheric assumptions that must be satisfied for the flux estimate to be valid: (i) horizontal flux divergence (Section 5.1): quasi-steady conditions, closed horizontal control surface, co-spatial CO₂ and wind measurement; (ii) the vertical plume method (Section 5.2): scanning curtain perpendicular to mean wind, uniform CO₂ background across curtain, CO₂ chemically inert; and (iii) atmospheric inversion (Section 5.3): linear transport model, correctly characterized prior uncertainties, Gaussian uncorrelated observation errors.

5.1. Horizontal Flux Divergence (Sector-Wise Flux)

In this mode, the LiDAR system performs scans across the horizon (e.g., a full 360° or specific sectors) at a roughly fixed altitude. Assuming no influx from outside the given area for the CO₂ concentration around part of the city and the horizontal wind vector, one can compute the net horizontal CO₂ flux out of that enclosed area (Figure 5). Mathematically, this is obtained by integrating the CO₂ concentration multiplied by the wind component normal to the boundary, all along the closed loop (sector boundary). In formula form, the horizontal flux F_{CO_2} through a boundary L is as shown in Equation (1):

$$F_{\text{CO}_2} = \int_L \rho(r) V(r) \cdot n dl \quad (1)$$

where

- ρ is CO₂ concentration (ppm);
- V is the horizontal wind velocity vector;
- n is the outward-pointing unit normal on the boundary;
- and dl is an infinitesimal segment of the boundary.

Essentially, this line integral sums the flux density $\rho(r) V(r) \cdot n$ (ppm·m s⁻¹) over the entire boundary length to get a total flux (ppm·m² s⁻¹), which can be converted to mass flux with known pressure/temperature. A positive F_{CO_2} indicates a net export of CO₂ out of the area (source behavior), whereas a negative value would indicate a net import (sink behavior). This approach implements the divergence theorem in a horizontal sense; if one encloses a city sector in a loop, the integral of V across that loop equals the net emission from that area (assuming steady state).

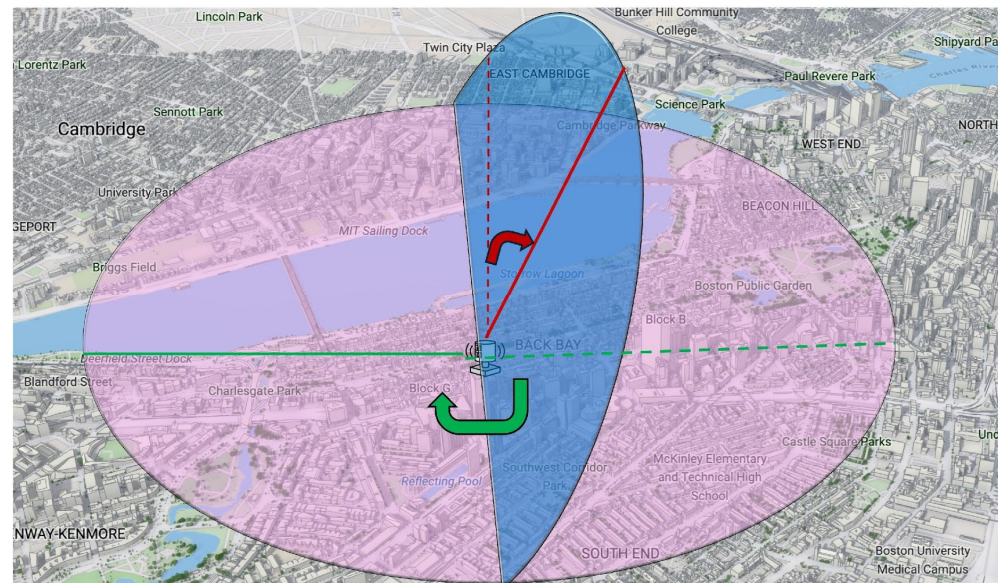


Figure 5. Conceptual scanning geometry for urban CO₂ flux estimation from an elevated DIAL platform in Boston, showing horizontal sector scans, indicated with green arrow (for perimeter flux) and vertical scanning slices, indicated with red arrow (for plume-based emissions). Note: Horizontal sector scans (solid arc sweeps in figure) produce azimuthally resolved CO₂ concentration maps at the scan elevation and are used with the horizontal flux divergence or inversion methods. Vertical curtain scans (dashed planes at fixed azimuth, varying elevation) produce cross-sectional CO₂ profiles downwind of a specific source and are used with the vertical plume method. An operational urban DIAL system would use both modes depending on the application.

In practice, this method was demonstrated in Nanjing, China by partitioning a scanning LiDAR unit's 60° sector into different land-use areas (an industrial zone, a university campus, and an urban park) [31]. They combined a CO₂ DIAL scanner with a coherent Doppler wind LiDAR unit to measure concentration and wind concurrently. The net horizontal flux was computed for each sector using the above equation. The results were striking: the industrial sector showed a persistent positive flux (CO₂ being carried away downwind), whereas the park and campus sectors showed near-zero net flux (no significant CO₂ export). Over a 24 h period, the industrial area's average horizontal flux was on the order of $3.5 \times 10^5 \text{ ppm} \cdot \text{m}^2 \text{ s}^{-1}$, far higher than the park's $0.1 \times 10^5 \text{ ppm} \cdot \text{m}^2 \text{ s}^{-1}$. In more intuitive terms, one part of the city was acting as a strong CO₂ source, while the neighboring green area was roughly in balance (daytime plant uptake offsetting nighttime respiration). By performing such flux calculations in all directions around a city, a single scanning LiDAR system can thus estimate the total carbon budget for the urban atmosphere with the possibility of collecting near-real time data, effectively measuring the city's net CO₂ emissions by summing all outflows minus inflows.

It is important to note that accurate horizontal flux estimates require careful alignment and data quality. The wind and CO₂ concentration must be measured simultaneously and co-spatially along the scanning plane. Any error in wind speed or direction propagates directly into the flux calculation. Additionally, because the DIAL system reports CO₂ in mixing ratio (ppm), those values need to be converted to an absolute mass density (e.g., kg/m³ or mol/m³) using the known air density (from pressure and temperature) if one wishes to report flux in mass units. Despite these challenges, the horizontal flux divergence method has proven feasible. It essentially provides an operational carbon-monitoring tool: if a city's emissions decrease due to policies or other factors, one should observe a smaller net CO₂ outflow across its perimeter, measurable by this LiDAR method. This kind of urban

carbon budget monitoring was previously attempted only with sparse sensor networks and models; now, the LiDAR approach offers a much more direct and data-rich measurement.

5.2. Vertical Cross-Section Flux (“Plume” Method)

Similarly, an additional approach would be to use the LiDAR unit to scan in a vertical plane downwind of a specific source or urban district. Here, the DIAL system is aimed in an upward scanning vertical slice (for example, scanning in elevation while fixed in azimuth) so that it maps a 2D cross-section of the CO₂ plume carried by the wind, as illustrated in Figure 5. If this vertical plane is oriented perpendicular to the prevailing wind (so that the plume blows through the plane), one can integrate the product of CO₂ concentration and wind speed through the plane to directly compute the emission rate of the source upwind of the slice. In essence, the plane acts like an “invisible curtain” that measures how much CO₂ is passing through, which must equal the source’s emission (neglecting chemistry or deposition for CO₂).

The basic equation for the plume flux method is analogous to a mass balance of a cross-section. If x and z denote horizontal and vertical coordinates along the plane S , and $U \propto (x, z)$ is the component of wind perpendicular to the plane at each location (i.e., the transport speed through the curtain), then the emission rate Q_{CO_2} (flux through the plane) is as shown in Equation (2):

$$Q_{\text{CO}_2} = \iint_S \rho(x, z) U(x, z) dx dz \quad (2)$$

where

$\rho(x, z)$ is the CO₂ concentration (mass per volume, or molar density) at point (x, z) in the slice.

In practice, the integration is taken over the full cross-sectional area of the plume as measured (from ground up to the plume top, and across the plume’s width). If the LiDAR unit measures mixing ratio, the background concentration is typically subtracted and the remainder converted to mass density. The above equation yields the total mass flow rate of CO₂ through the plane (kg/s or moles/s). This technique is essentially the same as the aircraft mass balance method that has been used in research flights: an aircraft traces a curtain downwind of a city or power plant, measuring the excess CO₂ in the plume and the wind, and from that computes the source’s emission rate [60]. Ground-based LiDAR can achieve the same without needing a flight, and it can do so continuously over time.

As with the horizontal flux, there are important caveats. The wind must be accurately known across the plume cross-section (Doppler wind LiDAR units or co-located anemometer arrays can provide this). Turbulence can cause the instantaneous plume to be irregular; averaging over longer periods or multiple scans may be needed for stable results [60]. Also, the LiDAR unit’s vertical scanning range may be limited; extremely tall plumes or very high atmospheric layers might escape the scan if the laser cannot tilt high enough or loses signal at altitude. Despite these challenges, this plume method is a powerful way to attribute emissions to specific sources (e.g., a power plant, an urban center, or even a highway) by directly capturing their CO₂ output in the downwind air. This plume method has already been validated for a geological CO₂ source: scanning hard-target DIAL system was used to topographically reconstruct a 2-D CO₂ field and calculate total flux from an active volcanic vent [37], demonstrating that the approach is feasible at spatial scales comparable to urban city blocks.

5.3. Inverse Modeling and Data Assimilation for Flux Maps

Both the horizontal divergence and vertical plume methods described above involve relatively direct integrations of observed data. A more advanced (and computationally

intensive) approach is to assimilate the rich dataset from an urban CO₂ LiDAR system into an atmospheric inversion model to solve for spatially distributed surface fluxes. In other words, rather than just calculating net flux for a given curtain, one uses many observations (hundreds or thousands of LiDAR-derived CO₂ concentrations at different points and times) and searches for the underlying emission map that best explains those observations given the physics of atmospheric transport. This is the essence of top-down Bayesian inversion or data assimilation in carbon monitoring.

In an inversion framework, one typically defines a vector x representing the unknown CO₂ fluxes in each grid cell (covering the city and surroundings), and a vector of observations y representing the CO₂ concentrations measured by the LiDAR system (and potentially other instruments). These are related by a transport model (often linearized around a background state), as shown in Equation (3):

$$y \approx Hx + \varepsilon \quad (3)$$

where ‘ H ’ is the sensitivity matrix (or source–receptor matrix) that encodes how emissions in each grid cell contribute to the concentration at each observation point and represents measurement and model errors. The inverse problem is to adjust the fluxes ‘ x ’ until the modeled concentrations ‘ Hx ’ match the LiDAR observations. This is usually solved by minimizing a cost function (imposing that the solution should not deviate too far from prior emission estimates within their uncertainties). The key point is that a scanning LiDAR system provides orders of magnitude more CO₂ data points (distributed in space and time) than a traditional sparse sensor network, so it can greatly improve the resolution and confidence of the inversion results. Ref. [61] conducted a high-resolution inversion for CO₂ fluxes in the Tokyo metropolitan area, using a combination of aircraft, tower, and surface data. They noted that traditional global inversion models struggled to constrain city-scale emissions at fine scales, and that model resolution on the order of 1 km is desirable for urban flux estimates (at coarser resolutions, the model cannot represent sharp concentration gradients near sources or the complex winds in a city.) Lagrangian dispersion models coupled with high-resolution weather models are often used to generate the matrix ‘ H ’. When fed with dense observations, such models can “invert” for the spatial pattern of emissions, for example, distinguishing industrial zones from residential or vegetated areas. In the future, a scanning LiDAR system could provide these dense observations (with ~100 m spatial resolution and frequent updates), fulfilling the data needs for urban inversions. Early studies [61–64] have shown that even with sparse monitors, atmospheric inversions can detect changes in urban emissions on monthly timescales. With a LiDAR setup, this could be pushed further, potentially resolving emissions changes hour by hour in different districts of the city.

6. Challenges and Future Directions

Deploying horizontal CO₂ LiDAR in urban environments has several challenges. Below, we outline key challenges and potential future directions to overcome them.

6.1. Instrument Cost and Complexity

DIAL systems have historically been expensive, typically ranging between 100 K and 500 K USD depending on specifications and application. High-performance lasers, detectors, and precision optics can drive system costs into the hundreds of thousands of dollars. This results in limited widespread adoption. A major future direction is cost reduction—using telecom industry components (DFB laser diodes, fiber amplifiers, etc.) to build lower-cost, smaller DIAL systems. Recent design studies suggest that a C-DIAL (Compact DIAL) could be built for under \$20 k by leveraging commercial off-the-shelf parts.

Simplifying the optical design (e.g., using direct detection instead of complex heterodyne setups) can also improve robustness. As costs come down, cities could afford networks of these sensors rather than one-off research instruments.

6.2. Eye Safety and Regulations

Operating a laser in populated areas raises safety concerns. Although 1.57 μm lasers are considered eye-safe, any high-power laser must be handled carefully. It is important to ensure that the beam does not dwell at low elevation angles where it could intersect with people or aircraft, as this could pose safety risks or cause distraction. Future systems will incorporate interlocks and aviation hazard integration (possibly shutting off automatically if, say, a low-flying helicopter is detected). Using scanning protocols that avoid dwell time over sensitive areas and conducting public outreach to explain the safety measures will be important for acceptance.

6.3. Line-of-Sight and Urban Obstacles

City landscapes are complex, with tall buildings that can block or reflect the beam. A single LiDAR unit on a skyscraper might still have blind spots behind other high-rises. One way to address this is by deploying multiple LiDAR units at different locations to cover each other's gaps (a networked approach). Alternatively, a scanning strategy can include slight variations in elevation angle to peek above or below obstacles if needed. In the future, one could envisage an array of smaller LiDAR units distributed around the city (even on mobile platforms like vehicles or drones) that work in tandem to map CO_2 , essentially creating a tomographic reconstruction of the urban CO_2 field.

6.4. Weather and Environmental Factors

Rain, fog, and heavy pollution (aerosols) can attenuate the LiDAR beam and interfere with measurements. Water droplets and fog scatter the infrared light strongly, reducing range and accuracy. While light rain or haze can be compensated by stronger signals or averaging, downpour conditions might cause data gaps. Future systems could incorporate all-weather capabilities by using adaptive scanning (e.g., pausing during the worst conditions, or using shorter-range vertical scans during fog). There is also research into using longer wavelengths ($\sim 2 \mu\text{m}$ or $10 \mu\text{m}$ CO_2 lines), which might penetrate fog a bit better, but those require new laser technology. Another environmental factor is background sunlight—daytime operations introduce noise from solar radiation. However, the use of narrowband filters and photon-counting detectors has proven effective, such that current DIAL prototypes can run 24/7 even in daylight.

6.5. Calibration and Accuracy

Ensuring that the LiDAR sensor's CO_2 readings are accurate (within a few ppm) across varying conditions requires robust calibration. This is challenging because the instrument might drift with temperature or alignment changes. Regular calibration using known reference cells or cross-comparison with standard sensors (NDIR gas analyzers, TCCON/Pandora column data) is needed. Future systems should employ automatic calibration routines, such as periodically scanning a sealed tube with a known CO_2 concentration or using atmospheric O_2 absorption as an internal reference (since O_2 is well-mixed and known). Moreover, converting the LiDAR sensor's measured optical data to absolute concentrations requires knowledge of atmospheric pressure and temperature along the path, so integrating auxiliary sensors or weather model data will improve accuracy. It has been demonstrated that CW-DIAL column retrievals can achieve sub-ppm agreement with co-located in situ measurements under field conditions [36], confirming that the DIAL

measurement itself is not the accuracy-limiting factor and proper calibration protocol can significantly improve measurements.

6.6. Data Processing and Flux Algorithms

A single scanning LiDAR sensor can generate massive amounts of data, potentially millions of individual range measurements per day. Processing this data, possibly in real time, into meaningful concentration maps and flux estimates is non-trivial. There are challenges in filtering noise, differentiating between real CO₂ enhancements and instrument artifacts, and doing so fast enough for near-real-time output. Future work will focus on streamlined data pipelines and perhaps machine-learning-based filtering to rapidly translate raw returns into clean CO₂ maps. On the flux estimation side, new algorithms are needed to handle the complex wind fields in cities and to attribute observed fluxes to surface processes. This might involve coupling the LiDAR data with high-resolution CFD (computational fluid dynamics) models of urban flow to interpret, for example, how a street canyon's emissions mix into the scanned air aloft. Ensemble empirical mode decomposition has been shown to separate CO₂-DIAL echo signals from noise more effectively than standard moving-average filters, reducing the effective detection limit by approximately 30% without increasing integration time [65].

6.7. Scaling to Other Gases and Multi-Species Monitoring

CO₂ is the one of the primary greenhouse gases, but cities also emit methane (CH₄, another major greenhouse gas) and pollutants like NO₂. The LiDAR approach can be adapted to these gases with different laser wavelengths. In fact, some research LiDAR systems already target CH₄ leaks using 1.64 µm lasers. A future direction could be to develop multi-species DIAL systems or co-located LiDAR units that together give a more comprehensive picture of urban greenhouse gases and air quality. For instance, a CO₂ DIAL unit could operate alongside a CH₄ DIAL unit, sharing some infrastructure. This would allow cities to track co-emitted gases and better understand emission sources (e.g., distinguishing CO₂ from combustion vs. CH₄ from natural gas leaks).

6.8. Uncertainty Considerations

Accurate CO₂ flux estimates from a horizontal scanning DIAL system require careful assessment of the full uncertainty chain. Seven principal sources are discussed below.

- (i) DIAL retrieval uncertainty. The CO₂ mixing ratio retrieved from the DIAL signal is uncertain due to photon noise, laser frequency instability, and errors in the differential optical depth calculation. At long ranges (>4 km), photon noise dominates and scales as the square root of the inverse of the detected photon count. Solar background radiation and detector dark counts set a noise floor that must be characterized through regular calibration scans against a sealed CO₂ reference cell or a hard retroreflector at a known distance. Achieving sub-ppm accuracy requires averaging over multiple scan repetitions, typically 10–30 min under moderate aerosol loading.
- (ii) Wind measurement uncertainty. Because CO₂ flux equals the product of CO₂ concentration and wind velocity, the wind measurement error propagates directly into the flux estimate for all three methods. Doppler LiDAR systems at 1.5–2 µm achieve wind speed precision of approximately ± 0.3 – 0.5 m/s [27]. At a mean urban wind speed of 5 m/s, this corresponds to a 6–10% fractional uncertainty in the flux. Errors in wind direction of ± 2 – 5 degrees introduce an additional error in the normal-to-curtain flux component for the plume method, particularly when the measurement curtain is not exactly perpendicular to the mean wind.

- (iii) Atmospheric transport uncertainty. For the inversion method (Section 5.3), the source-receptor matrix H must correctly represent how CO_2 from each source within the scan domain is transported to the measurement boundary. Urban dispersion models carry approximately 10–25% uncertainty, driven by incomplete knowledge of the 3D wind field, building-canyon turbulence, and mesoscale flow structures. This uncertainty affects the inversion method but is largely avoided by the direct integration methods (Sections 5.1 and 5.2), which do not rely on a transport model.
- (iv) Background CO_2 reference. Urban CO_2 enhancements above background are typically 3–20 ppm. The background CO_2 itself varies by 5–15 ppm seasonally, 2–5 ppm over a diurnal cycle, and 1–3 ppm due to synoptic transport changes. An error in background attribution propagates directly into the excess concentration used in the flux calculation. Best practice is to dedicate one or more DIAL beams toward the prevailing upwind direction to continuously measure inflow background CO_2 , updating it at the start of each scan cycle as wind direction rotates.
- (v) Planetary boundary layer (PBL) height. The horizontal flux integral (Equation (1)) requires integration over the full depth of the PBL, which grows from ~50–200 m under stable nocturnal conditions to >1500 m during convective midday periods. An error in PBL height translates directly and proportionally into an error in total flux. A ceilometer, aerosol backscatter LiDAR unit or radiosonde program must be operated in parallel with the CO_2 DIAL system to constrain PBL height at the temporal resolution of the scan cycle.
- (vi) Building-blocking gaps. In a dense urban environment, building obstructions can prevent measurement in 20–40% of the azimuthal scan from a single rooftop. These gaps in the boundary integral (Equation (1)) lead to systematic underestimation of total horizontal flux if not corrected. Mitigation strategies include spatial interpolation of CO_2 across blocked sectors using the measured concentration on adjacent unblocked beams, deployment of a second scanner at a complementary rooftop location, or explicit estimation of the unsampled flux contribution from a dispersion model applied only to the gap sectors.
- (vii) Steady-state assumption violations. The horizontal flux divergence method assumes that atmospheric conditions are quasi-steady over the scan averaging period (typically 15–60 min), meaning the local CO_2 tendency is small. This assumption breaks down during frontal passages, sea-breeze transitions, drainage flows, or any rapid change in wind direction that alters the CO_2 background faster than the scan cycle. Such violations can introduce flux biases of 10–50% depending on the rate of change. Quality-control filtering based on within-scan variability of wind direction and background CO_2 is recommended to flag and exclude affected averaging periods.

In summary, while challenges exist in deploying LiDAR for urban CO_2 monitoring, none appear insurmountable. Technological trends (laser cost reduction, better detectors, computational power) are rapidly addressing many of the current limitations. The path forward involves engineering solutions for reliability and ease-of-use, as well as strategic deployment (perhaps starting with pilot installations in a few cities to demonstrate the value). As these systems become more common, we anticipate an evolution from one-off experiments to an operational network of urban CO_2 LiDAR systems feeding data to city climate programs.

7. Conclusions

LiDAR-based CO_2 monitoring is poised to transform our understanding and management of urban carbon emissions. By providing direct, high-resolution observations of CO_2 in the air, LiDAR bridges the gap between satellite overviews and point-based ground

sensors. We can now observe the urban carbon cycle in action: observe plumes form and dissipate street by street and detecting the subtle breathing of a city's green spaces. Early demonstrations in cities have proven that DIAL can map CO₂ concentrations with tens of meters resolution and capture emission differences between neighborhoods. This new capability arrives at a crucial time: as cities worldwide pledge to reduce emissions, they need better tools to measure progress and pinpoint problem areas. A DIAL system atop a city building effectively turns the atmosphere into a transparent screen displaying where carbon is being emitted or absorbed. This review establishes three findings as follows: First, there is a quantifiable monitoring gap at the urban neighborhood scale (100 m to 10 km, 15 min to 1 h) that no currently deployed monitoring system can fill. This gap matters because it is the scale at which city districts differ from each other, at which individual policy interventions (low emission zones, building retrofit programs, traffic management changes) produce measurable CO₂ changes, and at which district-level emission inventories can be independently checked. Second, horizontal scanning DIAL at 1.57 μ m using SNSPD detection is, as far as we can determine from the published literature, the only measurement approach that can fill this gap, because it combines the necessary spatial resolution, temporal sampling rate, direct flux measurement capability, and potential for continuous unattended operation. Third, the main barrier to operational deployment is not scientific but engineering and institutional: the detection technology (SNSPD) and laser source (fiber CPA at 1.57 μ m) are both at prototype readiness, and the flux estimation methods are validated; what is missing is long-term detector stability in unattended rooftop conditions, real-time processing pipelines, and building-access logistics.

The state-of-the-art will continue to advance, with systems becoming more affordable, automated, and possibly widespread as part of smart city infrastructure. In a not-so-distant future, one can imagine each major city having a network of compact CO₂ LiDAR units continuously scanning, much like weather radars do for storms. They would provide an ongoing audit of urban emissions, verify whether mitigation strategies are truly working, and even issue alerts if unexpected CO₂ spikes occur (for example, from industrial upsets or anomalous traffic jams). Furthermore, the data from urban CO₂ LiDAR units will enrich scientific models, leading to better forecasts of urban CO₂ levels and improved inversion estimates of emissions. Importantly, these measurements lend transparency and credibility to climate action—city leaders can base policies on observed data and the public can see evidence of changes in their air.

In conclusion, LiDAR-based approaches for urban CO₂ monitoring represent a paradigm shift from sparse sampling to imaging of urban greenhouse gases. They empower us to observe the fine-grained mosaic of sources and sinks that make up a city's carbon footprint. While challenges of deployment and integration remain, the progress to date indicates that these are being overcome with innovation in photonics and data science. By “dialing in” to CO₂ and other gases, cities will gain a powerful, evidence-based tool to guide their journey toward lower emissions and healthier atmospheres, effectively illuminating the path to carbon-neutral urban futures.

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