Low-cost autonomous chambers enable high spatial and temporal resolution monitoring of soil CO_2 exchange across landscapes

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Abstract

1. Soil CO_2 flux is a critical component of ecosystem carbon cycling, but due to high cost and mechanistic constraints, existing measurement systems are often limited by trade-offs between resolution (temporal and spatial), and spatial coverage. These constraints hinder efforts to monitor soil fluxes across diverse, heterogeneous landscapes and environmental gradients.
2. We developed Fluxbot 2.0, a low-cost, autonomous chamber system capable of continuous, distributed soil CO_2 flux measurements without external power or infrastructure. To assess its capability to capture landscape-scale variability, we deployed two Fluxbot 2.0 arrays, one at each of two hemlock forest sites in Harvard Forest, Massachusetts, USA, and compared its estimates of flux to those from existing, well-established automated chamber arrays that rely on multiplexed chambers and high-accuracy CO_2 analyzer units.
3. Fluxbots successfully captured site means, spatial variability, temporal patterns, and environmental responses, including temperature-driven flux dynamics. These measurements reflected differences in forest conditions between two sites and showed that distributed arrays of low-cost sensors can effectively capture both fine-scale variability and broader patterns across a landscape.
4. By enabling low-cost, autonomous monitoring of soil carbon flux in strategically distributed arrays, Fluxbot 2.0 addresses key gaps in existing soil CO_2 flux datasets. The system facilitates measurements across environmental gradients and heterogeneous landscapes, supporting research on soil carbon dynamics and biotic interactions that influence carbon cycling.

1. Introduction

Soil respiration, hereafter soil carbon (C) flux, is the largest terrestrial source of carbon dioxide (CO_2) to the atmosphere, accounting for over 90 Pg C annually (Bond-Lamberty and Thomson 2010; Hashimoto, Ito, and Nishina 2023), the majority of gross terrestrial ecosystem emissions (Friedlingstein et al. 2025). It is an essential component of accurate ecosystem carbon budgets, allowing researchers to describe fluxes and feedbacks between terrestrial ecosystems and the atmosphere. Soil CO_2 flux is significantly variable across temporal scales (from diurnal to seasonal), spatial scales (from centimeters to kilometers) (Vargas et al. 2011; Bradford and Ryan 2008), and across topography, vegetation, and disturbance patterns (Rodeghiero and Cescatti 2008), requiring high spatial and temporal resolution as well as broad spatial coverage in data collection to characterize accurately.

Recent studies highlight how landscape heterogeneity across scales from centimeters to kilometers fundamentally influences C fluxes (Premke et al. 2016). Factors like microtopography, individual plant species, and species assemblages create localized element cycling hotspots, requiring high resolution monitoring (Jevon et al. 2023; Keiser et al. 2024). Spatial variability and temporal fluctuation in soil moisture and chemistry can lead to hot spots and hot moments of soil fluxes in natural environments (Gachibu et al. 2023; Leon et al. 2014; K. Savage, Phillips, and Davidson 2014). Land use change through urbanization and ecosystem fragmentation can influence spatial patterns in soil CO_2 flux across overlapping gradients with additive or synergistic effects (Garvey et al. 2022; Reinmann et al. 2020). Fauna, from small soil dwellers to megafaunal ecosystem engineers, can further induce spatial heterogeneity. Animals, both wild (e.g.,(Ohashi et al. 2007; Saunders et al. 2023) and domestic (e.g., (Ondier et al. 2020), and changes to those communities (E. S. Forbes et al. 2019) require spatially distributed and/or spatially dense measurements to capture species' heterogeneous effects on soil C cycling across scales (DeCarlo and Caylor 2019; Ferraro and Lienau 2025; Schmitz et al. 2018; Risch et al. 2013).

Through time, these processes vary and are modulated by daily cycles in edaphic conditions (e.g. (E. Forbes et al. 2023; Tang, Baldocchi, and Xu 2005; Kathleen Savage et al. 2009; Huang et al. 2020; K. Savage, Phillips, and Davidson 2014), seasonal change (Giasson et al. 2013; E. A. Davidson et al. 2006) , and changing climate (Raich, Potter, and Bhagawati 2002; Carey et al. 2016). Beyond its utility for parsing ecologically-specific questions, high-resolution soil carbon flux monitoring also supports data-driven approaches for carbon offset projects and credit programs in contexts like agroecology (Kim et al. 2025; Paustian et al. 1997, 2000, 2016), which would move efforts away from current estimation-based methods (Novick et al. 2022).

To capture variability in soil carbon flux, researchers use a range of gas analysis methods and associated tools. Hand-held, manually-operated "survey" chambers with precision gas analyzers can capture detailed spatial patterns in soil CO_2 flux through distributed sampling, but due to cost and labor constraints provide limited temporal resolution or reliable comparisons across large spatial extents. Commercial automated chambers provide excellent temporal resolution but are prohibitively expensive (often >$20,000 USD per system), limiting deployments to small numbers of chambers at single locations (K. E. Savage and Davidson 2003). Eddy covariance towers monitor ecosystem-scale fluxes with high temporal resolution and large spatial extents, but lack spatial resolution needed to identify specific drivers of flux variability (Hollinger et al. 2004) . In all cases, logistical constraints prevent researchers from asking questions that interrogate high spatial resolution, temporal resolution, and spatial scale simultaneously (E. Forbes et al. 2023; Pan et al. 2024).

While measurement precision and instrument durability are important considerations, soil CO_2 flux monitoring objectives may benefit from trading some precision for greatly expanded coverage through distributed arrays of autonomous devices. Advances in low-cost CO_2 sensors enable new approaches to ecosystem gas exchange data collection centered around replication (Pereira and Ramos 2022). Building on our previous work developing the original Fluxbot—a low-cost, autonomous soil CO_2 flux chamber system (E. Forbes et al. 2023; Pan et al. 2024)—we present here the first landscape-scale validation of a low-cost, automated and near-continuous array of Fluxbot 2.0 autochambers. Fluxbot 2.0 aims to further address key data gaps with capabilities that enable more access to high-resolution soil CO_2 flux monitoring across heterogeneous contexts.

We validated two distributed arrays of Fluxbot 2.0 and directly compared their outputs with those from two established arrays of automated flux chambers at the Harvard Forest, where multiplexed automated chambers (or, autochambers) coupled to traditional high-precision flow-through infra-red gas analyzers (IRGA) have been continuously monitoring soil CO_2 flux in contrasting forest stands for over a decade. We assess the performance of Fluxbot 2.0 relative to the established autochambers under field conditions, demonstrating their scalability and ability to accurately detect fluxes across spatially heterogeneous and dispersed locations.

2. Methods

We worked in two eastern hemlock (*Tsuga canadensis* L.) forest stands approximately 1.4 km apart at the Harvard Forest Long Term Ecological Research (LTER) Site in Petersham, Massachusetts, USA. The two stands, located at 42.541500, -72.174624 (stand 1) and 42.529162, -72.178581 (stand 2) were infected by the hemlock woolly adelgid (HWA; *Adelges tsugae*) in 2009 after initial detection at the site in 2008, and selected for long-term monitoring due to their contrasting responses to infection. A set of six automated soil respiration chambers were established in each stand in the mid 2010s and have since been continuously monitoring soil CO_2 flux. Within each stand, six units of Fluxbot 2.0 were deployed within the footprint of the established autochamber array, to allow direct comparison; two additional units of Fluxbot 2.0 were deployed at each (eight total per stand) as backups to ensure data continuity.

2.1. Site/context description

In the fall of 2015, six automated soil respiration chambers were established within the footprint of the Hemlock tower (42.529162, -72.178581) at Harvard Forest LTER. The hemlock tower stand (hereafter “stand 2”) has distinct hemlock loss and high stand biodiversity in overstory and understory plant communities. A second set of six chambers were established in May 2016 downstream from the Bigelow Brook weir (42.541500, -72.174624). Contrary to stand 2, this stand (“stand 1”) continued to resemble an uninfected hemlock stand in hemlock loss and community composition despite infection.

2.2. Harvard Forest autochambers

The six autochambers per site are arrayed in a circle around a control box. The collars are 7cm long segments of schedule 80 PVC pipe installed approximately 3 cm into the soil; PVC diameter is approximately 10 inches. Chamber lids open and close pneumatically every 30 minutes using AC line power.

The control box at the center of each autochamber array includes the infrared gas analyzers (IRGA) and power equipment. The IRGA at the hemlock tower is a LI-840 (LI-COR Lincoln, NE, USA), and at Bigelow Brook is a LI-800 (LI-COR). The other mechanics include a pump (Brailsford TD-3LS 12VDC), a CR1000 datalogger, a SDM-CD16AC relay controller, and a 12VDC power supply. Critically, the chambers are plumbed to an array of solenoid valves also at the control box, that move compressed air to and from the pistons that open and close the chamber lids and move sampled air from the chambers to the IRGA. The chambers are activated sequentially every 5 minutes to enable measurement at each of the six chambers, every 30 minutes. Each measurement lasts for five minutes total: for the first 45 seconds, the chamber lid remains open and air is drawn at 1 liter per minute. The lid then closes and internal CO_2 concentration is recorded at 1hz rate for four minutes, 15 seconds. At the completion of each five-minute measurement cycle the chamber lid reopens.

The LI-840 at stand 2 measures CO_2 and H_2O and applies a correction for water vapor in the sample air. The LI-800 at stand 1 does not correct for water vapor automatically. A subset of historical flux measurements from the LI-800 were recalculated using the water vapor correction applied to simultaneously-collected LI-840 data. The correction underestimated the fluxes by only 0.016% ± 2%; as a result, the LI-800 data does not include a correction factor.

Photo 1 | Field deployment of soil CO_2 flux monitoring systems at Harvard Forest. The image shows both Fluxbot 2.0 and autochamber systems deployed side-by-side in a hemlock forest stand. The larger pneumatically-operated autochambers are connected via tubing to a central control box containing the infrared gas analyzer (IRGA), while the smaller autonomous Fluxbot 2.0 units operate independently with integrated CO_2 sensors and servo-actuated lids. The inset shows a close-up of a Fluxbot 2.0 unit with its hinged lid design and compact, battery-powered configuration. This co-located deployment enabled direct comparison of flux measurements between the two systems under identical field conditions.

2.3. Fluxbot array

Eight Fluxbot 2.0 chambers were deployed at each of the two sites at Harvard Forest. Six Fluxbots were paired with autochambers to enable direct comparisons of flux measurements, while two additional units were deployed as backups to ensure continuity in case of system failure, such that eight fluxbots were distributed approximately evenly throughout the plot. Fluxbots were installed on 4-inch SCH 40 PVC collars inserted approximately 4 cm into the soil. The chambers, constructed from commercially available PVC sewer caps with hinged lids, were actuated by servo motors on a 60-minute cycle. During each cycle, the lids closed to create an airtight environment for soil CO_2 flux measurements and reopened to restore ambient conditions between measurements. Fluxbots were positioned within each site to capture local heterogeneity in microtopography and vegetation. This distributed configuration ensured that flux variability across the array was representative of site-scale conditions.

Each Fluxbot was equipped with a Senseair K30 nondispersive infrared (NDIR) CO_2 sensor inside the chamber lid, which measured CO_2 accumulation within the closed chamber diffusively (i.e., not plumbed from the exterior to the interior with tubing and a fan). The K30 has a detection range of 0–10,000 ppm; for each measurement period at the end of each hour, they were set to record at a frequency of 1Hz for six minutes total (one minute while chamber is open to capture ambient CO_2 concentration; five minutes while chamber is closed to capture accumulation). Environmental conditions were monitored with a Sensirion SHT-30 (air temperature and relative humidity) and an LPS22 (barometric pressure), both deployed adjacent to the K30 inside the chamber lid. Each Fluxbot was powered by a Voltaic Systems V50 battery pack, which provided up to 13 days of continuous operation before needing recharging. Data collection, sensor operation, and lid actuation were managed by a Particle Boron microcontroller, which also transmitted measurements hourly via LTE cellular networks to a Google Sheet document. The modular, independently-operating, and weatherproofed design (including PTFE envelopes around the K30 sensor to prevent condensation, and reflective shields over the SHT to prevent errors in temperature detection from direct sunlight). A full description of system engineering and performance metrics is provided in (Pan et al. 2024).

The updated Fluxbot 2.0 boasts several improvements from the original design (E. Forbes et al. 2023). Battery life is extended from ~24hrs to >300hrs, and wireless data transmission capabilities allows for user monitoring from remote locations. Fluxbot 2.0 also has improved weatherproofing and simplified assembly, but maintains the core benefits of low individual cost (~400 USD in parts), independence (i.e., not multiplexed), and mechanistic reproducibility.

2.4. Fluxbot-chamber comparison experiment

The paired Fluxbot and autochamber systems were operated concurrently at each site to evaluate the performance of the Fluxbot system relative to the established autochambers under identical environmental conditions. Flux measurements from both systems were calculated from raw data, using the same standardized processing methods to ensure consistency. These comparisons were analyzed to assess whether Fluxbots could replicate the mean fluxes, temporal trends, and spatial variability observed with autochambers, addressing the study's broader goal of evaluating the scalability and ecological applicability of the Fluxbot system across diverse forest conditions.

2.5. Additional environmental data

Air pressure and soil temperature data used in this study were obtained from the Fisher Meteorological Station at Harvard Forest (Harvard Forest Data Archive: HF001). The station, located at 42.53311°N, -72.18968°W, is approximately 1.55 km from stand 1 (Bigelow Brook

Weir) and 1.01 km from stand 2 (Hemlock Tower). Air pressure was measured using a Vaisala CS105 barometer, and soil temperature at 10 cm depth was recorded using Campbell Scientific 107 probes. For this study, we used average hourly values to align with the temporal resolution of fluxbot measurements. These data are publicly available as part of the Harvard Forest LTER) program and are accessible via the Environmental Data Initiative (Boose and VanScoy 2025).

2.6. Data processing and calculation

Raw data (e.g., times series of CO_2 concentrations for each observation interval) was converted to flux for each array in the following manner. One minute of raw concentration data is trimmed from the start of the five-minute chamber closure period to account for the "dead band", or period of time during and after chamber closure during which the interior volume is not yet thoroughly mixed (and detection of interior gas concentration is not yet reliable). The remaining four minutes of data are converted from ppm (concentration) to umol CO_2 (mass) using ideal gas laws, including chamber volume plus the internal volume temperature data collected from each chamber's accessory gas analyzers (Forbes et al. 2023), and atmospheric pressure data collected by the Fisher Meteorological Station (see above). Subsequently, change in CO_2 mass is determined by calculating both linear and quadratic regressions of these four minutes of data; the initial slope of each regression is then used to calculate change in CO_2 mass over the interval, over the area of the collar on which the chamber sits.

Fluxbot 2.0 array: Because the Fluxbot 2.0 has a relative humidity sensor inside the chamber, flux estimates included a humidity correction based on the density of water vapor inside the chamber volume over the course of a measurement interval. Fluxbot 2.0 chamber volume was (on average) 768cm^3; chamber area was 81cm^2.

Autochamber chamber volumes ranged from 9450cm^3 to 10450cm^3, while area for all chambers was 646.328cm^2. Because there was only a relative humidity sensor on one of the two control boxes, the flux estimates generated for the autochamber arrays were not corrected for humidity (see above).

3. Results

3.1. Temporal Trends and System Performance

During the October 2-31, 2024 deployment period, both Fluxbots and autochambers maintained high operational reliability, with data capture rates exceeding 95% despite periodic interruptions in power or data transmission. Both systems captured consistent temporal trends in soil CO_2 flux measurements. Figure 1 presents the calculated fluxes and rolling 6-day means, which interpolate across gaps caused by system downtime. Soil temperature at 10 cm depth, measured hourly, is shown alongside flux data and highlights environmental variability during the study period.

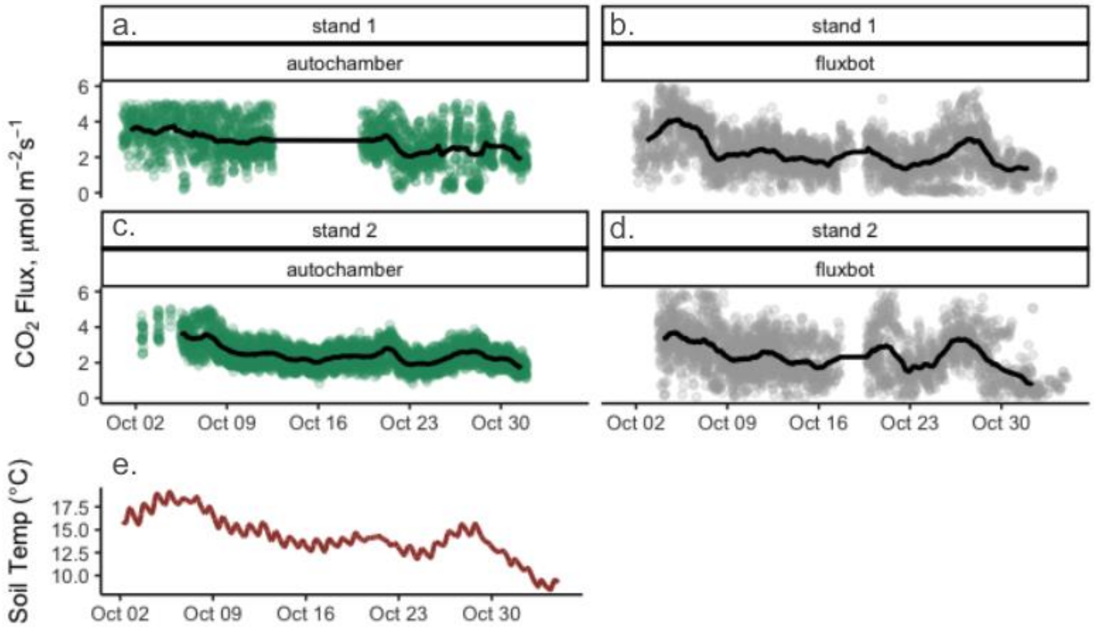

Fig. 1 | Panels a-d: Calculated fluxes and rolling mean for each array. Arrays were deployed from October 2-31, 2024 but experienced variable downtime, accounting for the data gaps seen here. Black lines are 6-day rolling means (filled with adjacent values during system downtime). **Panel e: Soil temperature from Fisher meteorological station.** Soil temperature measured hourly at 10cm depth and available through the Harvard Forest archive.

3.2. Chamber-Level Flux Distributions

Chamber-level analysis revealed consistent patterns in flux variability across both stands. Individual chamber medians ranged from approximately 1.5 to 4.0 μmol $m^{-2}s^{-1}$, with interquartile ranges spanning 0.9-4.4 μmol $m^{-2}s^{-1}$. The similar spread in chamber-level distributions between methods supports the equivalence of spatial characterization between systems.

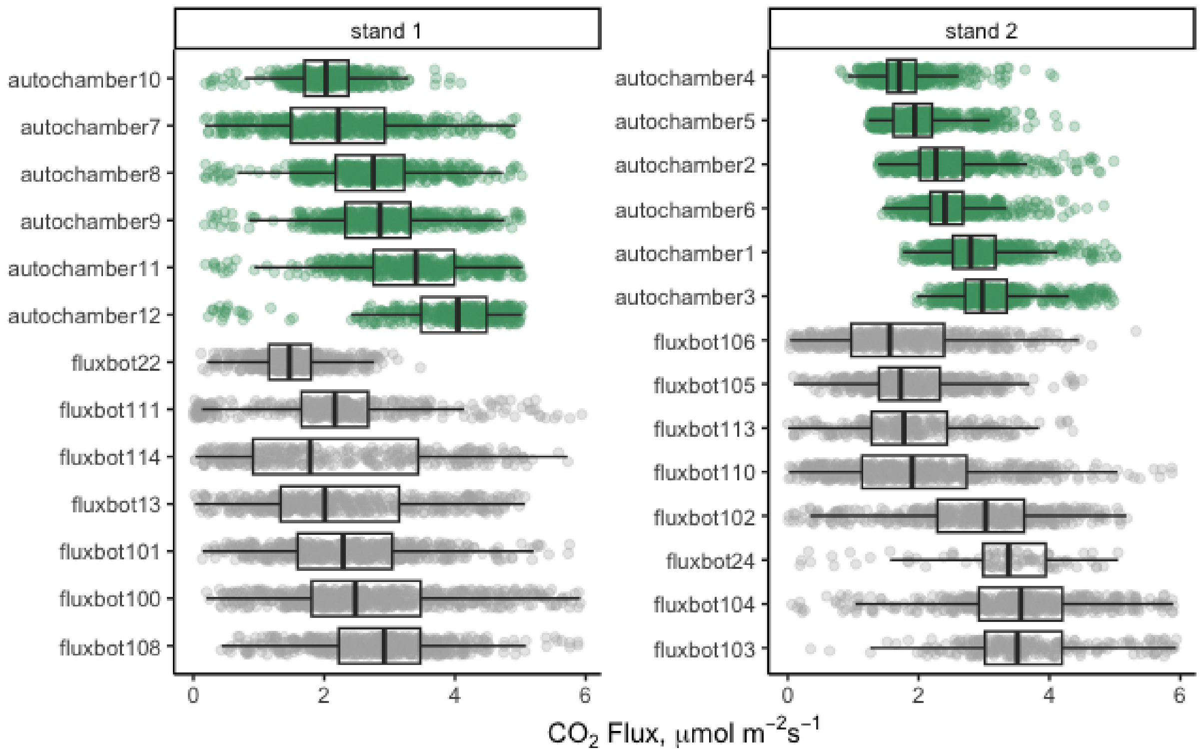

Fig. 2 | Distributions of chamber-level fluxes. Chambers are grouped by stand within separate plots for each array (fluxbots and autochambers). In each boxplot, the middle horizontal line represents the median flux value, while the upper and lower edges of the box mark the 75th and 25th percentiles, respectively (the interquartile range, IQR). The whiskers extend to the most extreme values within 1.5 times the IQR from the quartiles. Chambers are plotted in order from lowest to highest mean flux for ease of interpretation.

3.3. Statistical Validation and Model Performance

The generalized additive model (GAM) analysis provided robust statistical validation of the Fluxbot system, explaining 54.1% of observed variance (Figure 3). The GAM revealed no significant differences between stand 1 and stand 2 plots ($\beta = -0.006$, SE = 0.249, $p = 0.958$) or between arrays ($\beta = -0.193$, SE = 0.250, $p = 0.185$). Both temporal smoothing terms (hour of day and day of year) were highly significant ($p < 2e-16$), indicating strong temporal structure in the flux measurements.

Table X | Generalized additive model results for soil CO_2 flux measurements. The model includes fixed effects for forest stand (Stand 2 vs. Stand 1) and measurement method (Fluxbot 2.0 vs. autochamber), with smooth terms for hour of day, individual chamber identity, and soil temperature at 10 cm depth (s10t).

Parameter	Estimate/edf	Std. Error/Ref.df	t/F value	p-value
(Intercept)	2.68731	0.22411	11.991	<2e-16 ***
Stand 2	-0.01306	0.24887	-0.052	0.958
Method: fluxbot 2.0	-0.33194	0.25024	-1.326	0.185
s(hour(hour_of_obs))	6.367	7.516	15.69	<2e-16 ***
s(id)	23.926	24.000	356.24	<2e-16 ***
s(s10t)	8.180	8.735	792.91	<2e-16 ***

Model Summary: R-sq.(adj) = 0.541, Deviance explained = 54.3%, n = 13591 Significance codes: 0 " **0.001** " 0.01 " 0.05 '.' 0.1 ' ' 1

The GAM analysis revealed no significant differences between forest stands (p = 0.958) or measurement methods (p = 0.185), indicating that both hemlock stands exhibited similar flux patterns during the study period, and that Fluxbot 2.0 measurements were statistically equivalent to autochamber measurements. Given these findings, subsequent analyses pooled data across both stands to compare system performance (all autochambers vs. all Fluxbots).

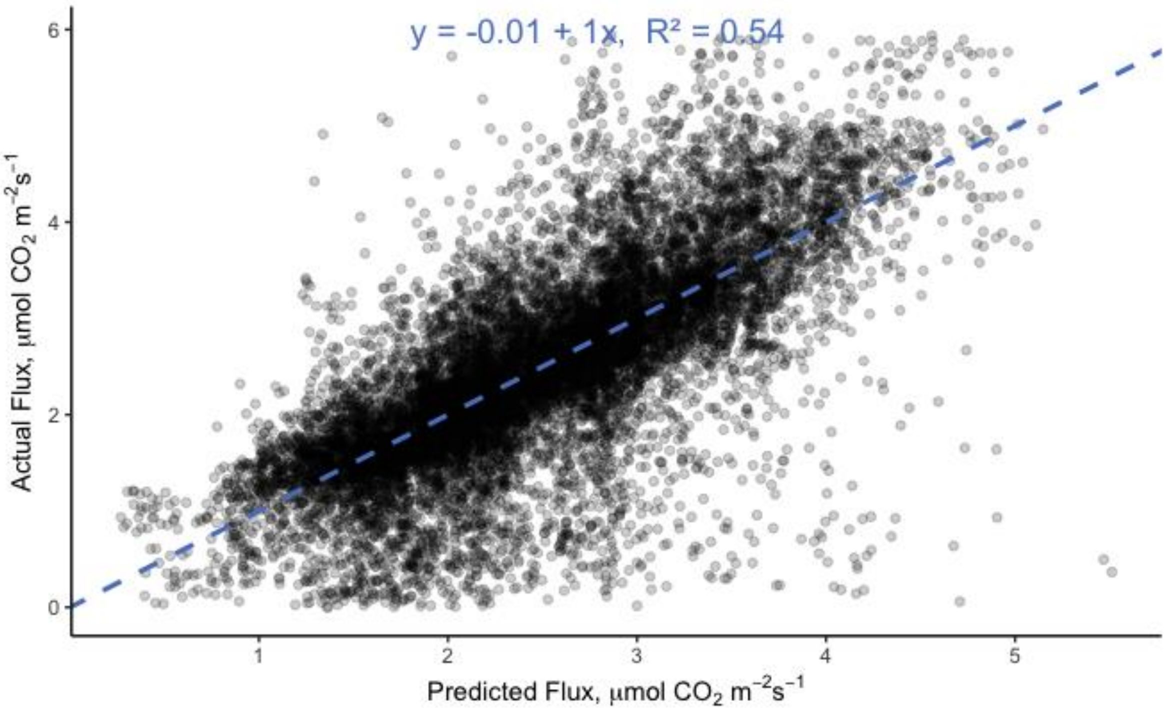

Fig. 3 | Modeled soil respiration across the entire dataset. Generalized additive model using fixed effect of stand and array method (fluxbot or autochamber); smoothed fixed effect of hour of day and day of year; and random effect of chamber ID. Scatterplot shows predicted vs. actual flux and hypothetical 1:1 line.

3.4. Measurement Distribution and System Agreement

The distribution of individual flux measurements showed strong concordance between systems (Figure 4). Both methods captured a similar range of flux values (approximately 0-6 μmol $m^{-2}s^{-1}$) with comparable central tendencies, illustrated by overlapping kernel density estimates. The slightly wider distribution in Fluxbot 2.0 measurements suggests marginally higher measurement variability, potentially due to the different sensor input employed (diffusion-based sensing within each unit, versus flow-through to a common IRGA for the autochambers), or the smaller area covered by the Fluxbot 2.0 collar footprint (4” diameter versus approximately 28” diameter of the autochamber collars).

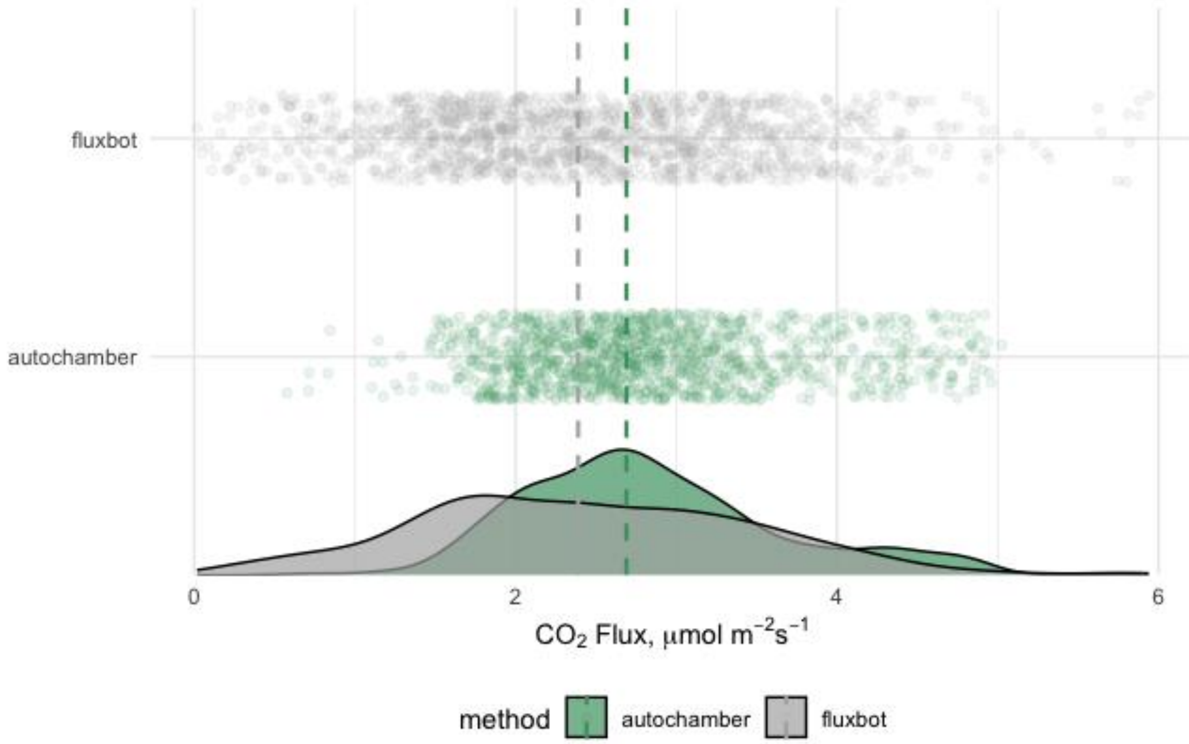

Fig. 4 |Scatterplot and density plot showing flux estimates from each array. The upper panel displays individual flux measurements from fluxbots (top) and autochambers (bottom) as jittered scatter points, with vertical dashed lines representing the mean flux for each method. The lower panel illustrates the kernel density estimates for the flux values from both methods, indicating the distribution of flux measurements. Fluxbot data are shown in grey, and autochamber data are shown in green. The vertical dashed lines indicate the respective mean flux values for each method. This visualization highlights both the distribution and central tendency of flux measurements from the two sensor systems.

Quantitative comparison of 3-hour rolling mean fluxes demonstrated strong agreement between systems (Figure 5). Lin's Concordance Correlation Coefficient (CCC) accounts for both precision and accuracy, providing a more comprehensive measure of agreement than simple correlation (R^2); a CCC value close to 1 indicates strong agreement between the systems (n.d.; Akoglu 2018). The 3-hour rolling mean demonstrated CCC of 0.7 and linear regression parameters of $y = -0.49 + 1.09x$ ($R^2 = 0.67$). The regression slope of 1.09 indicates minimal proportional bias, while the small intercept (-0.49) suggests negligible systematic offset between methods. The moderate R^2 value reflects natural variability in soil flux measurements rather than methodological disagreement, as evidenced by the tight confidence intervals around the regression line.

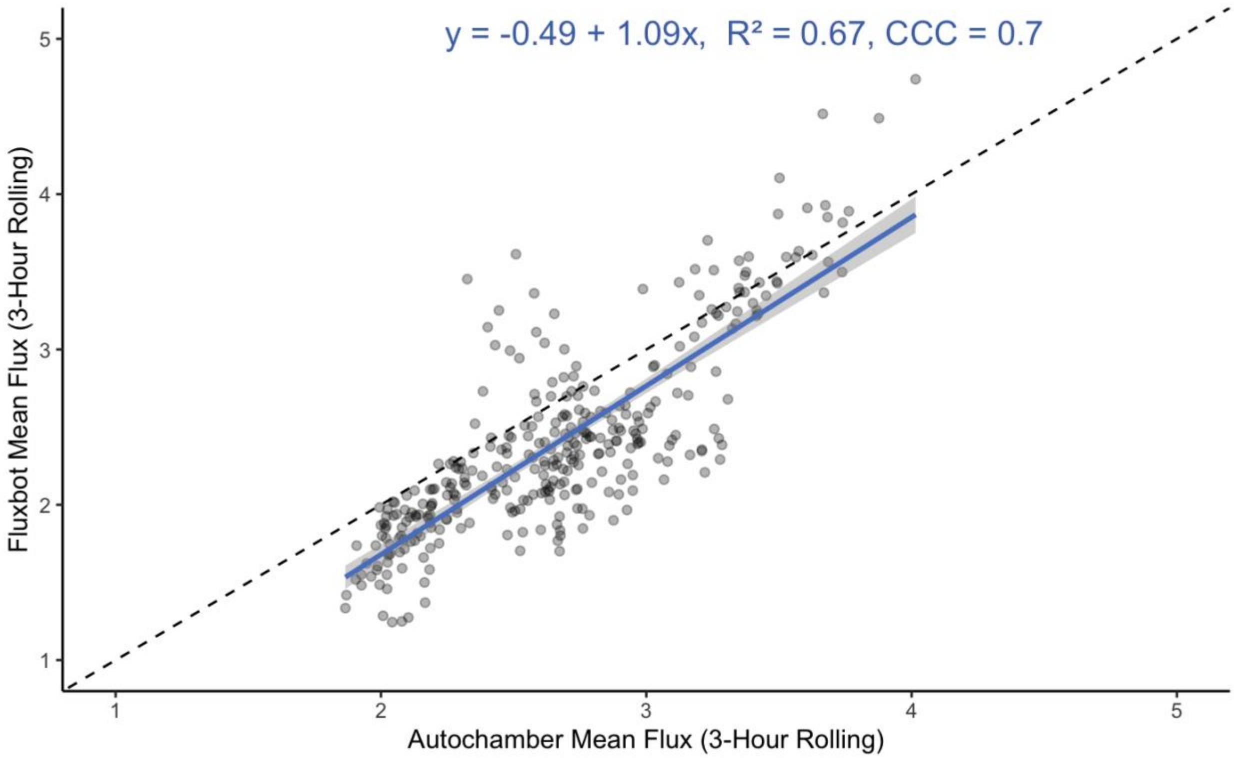

Fig. 5 | Agreement between array-wide mean fluxes. Scatterplot showing 3-hour rolling means of flux estimates from fluxbots and autochambers. Each point represents the paired rolling mean of flux measurements between the two sensor systems at the corresponding time intervals. The x-axis represents the 3-hour rolling mean flux from the fluxbots, while the y-axis represents the 3-hour rolling mean flux from the autochambers. The plot highlights the relationship and agreement between the two measurement systems across the observation period. The degree of agreement between the systems is quantified using Lin's Concordance Correlation Coefficient (CCC).

3.5. Diurnal Patterns and Temporal Dynamics

Both systems captured pronounced diurnal patterns in soil CO_2 flux (Figure 6), with remarkable consistency in the timing and magnitude of daily cycles. Peak fluxes occurred during midday hours (approximately 15:00-17:00 local time), reaching mean values of 2.7 ± 0.1 μmol $m^{-2}s^{-1}$, while minimum fluxes were observed in early morning hours (04:00-06:00) at around 2.3 ± 0.1 μmol $m^{-2}s^{-1}$. The 95% confidence intervals remained consistently narrow (±0.1-0.2 μmol $m^{-2}s^{-1}$) throughout the daily cycle for both systems, indicating high measurement precision and reproducibility.

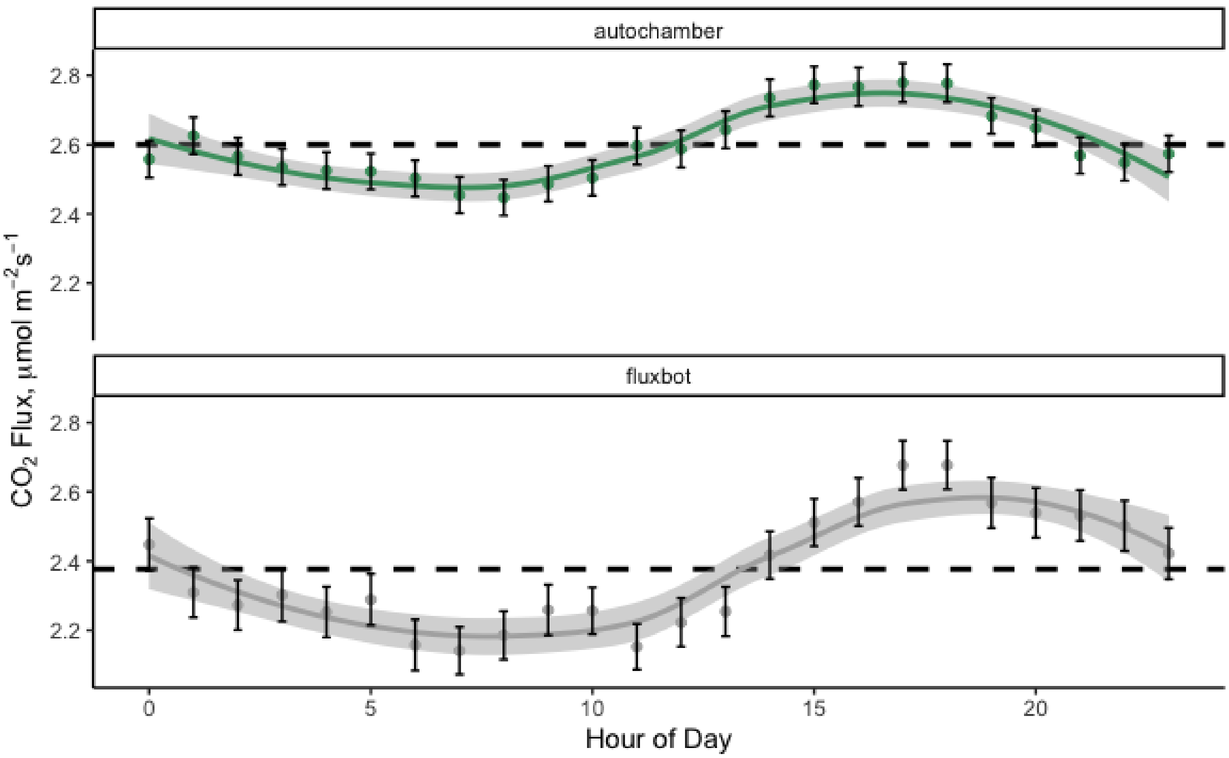

Fig. 6 | Diurnal variation in flux estimates measured by autochambers (top panel) and fluxbots (bottom panel) over the course of the day. The smooth lines represent the fitted trends with 95% confidence intervals (shaded areas) for each method, showing the diurnal pattern of fluxes. Points correspond to the hourly mean flux estimates, with error bars representing the standard error of the mean. The dashed black horizontal lines indicate the overall mean flux for each method.

3.6. Temperature Response

Temperature sensitivity analysis revealed comparable but slightly divergent Q10 values between systems (Figure 7). Autochambers exhibited a Q10 of 2.31 across an observed temperature range of 11.2-19.1, while Fluxbots showed a marginally higher Q10 of 2.86 across an observed temperature range of 8.5-19.1°C. This difference was not statistically significant ($p = 0.12$) and both values fall within the expected range for temperate forest soils. The relationship between soil temperature and flux was strongly linear on a log-transformed scale ($R^2 > 0.85$ for both systems), indicating robust capture of temperature-dependent respiration dynamics.

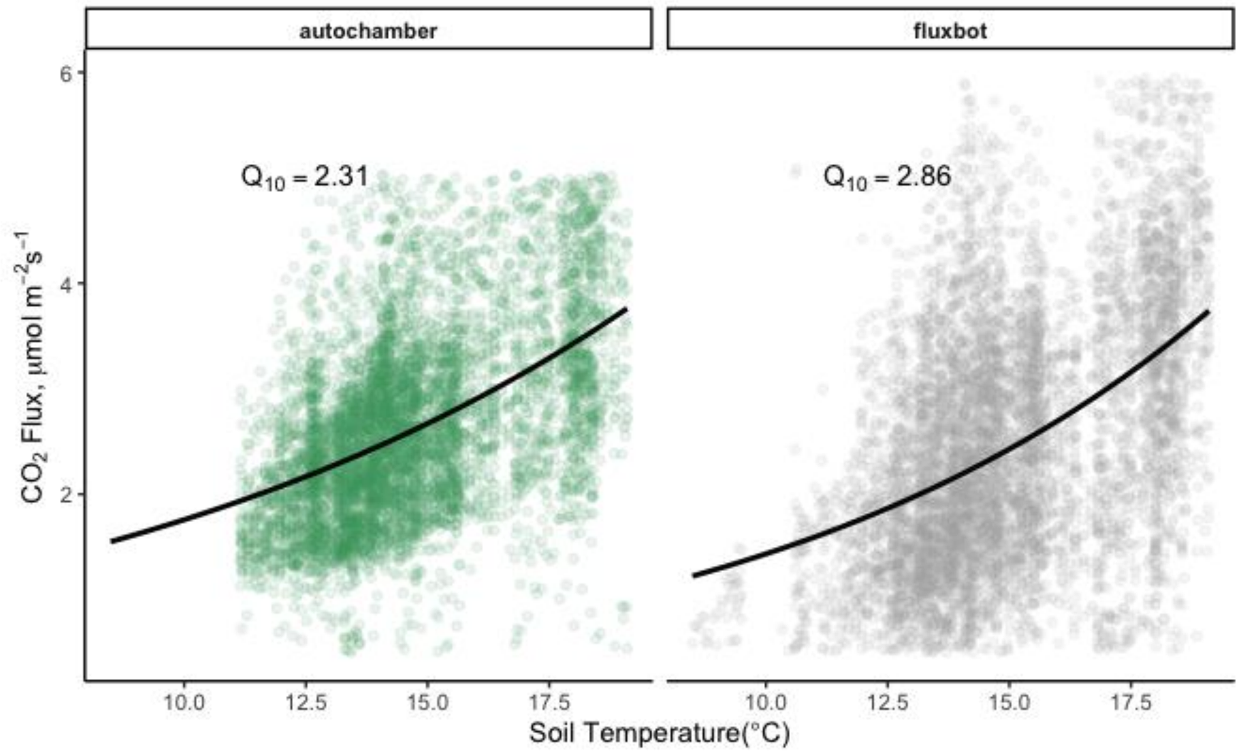

Fig. 7 | Scatterplot showing the Q10 models for soil respiration flux for Autochambers (green) and Fluxbots (grey). Solid line represents the fitted Q10 model for autochambers, and the dashed line represents the fitted Q10 model for fluxbots. Points indicate individual flux measurements.

3.7. Spatial Heterogeneity

Analysis of spatial variability using Lorenz curves revealed identical Gini coefficients of 0.13 for autochamber array, and only marginally more variable (0.16) for the Fluxbot 2.0 array (Figure 8), indicating almost consistent characterization of flux heterogeneity. This relatively low Gini coefficient suggests moderate spatial homogeneity in flux patterns, with approximately 60% of total measured flux coming from 50% of sampling locations. The relative agreement in Gini coefficients between methods provides strong evidence that Fluxbot 2.0 can effectively replicate the spatial resolution capabilities of traditional autochambers, and the slight difference in agreement is likely reflective of the smaller footprint of Fluxbot 2.0 compared to an autochamber, as the likelihood of capturing variation is higher.

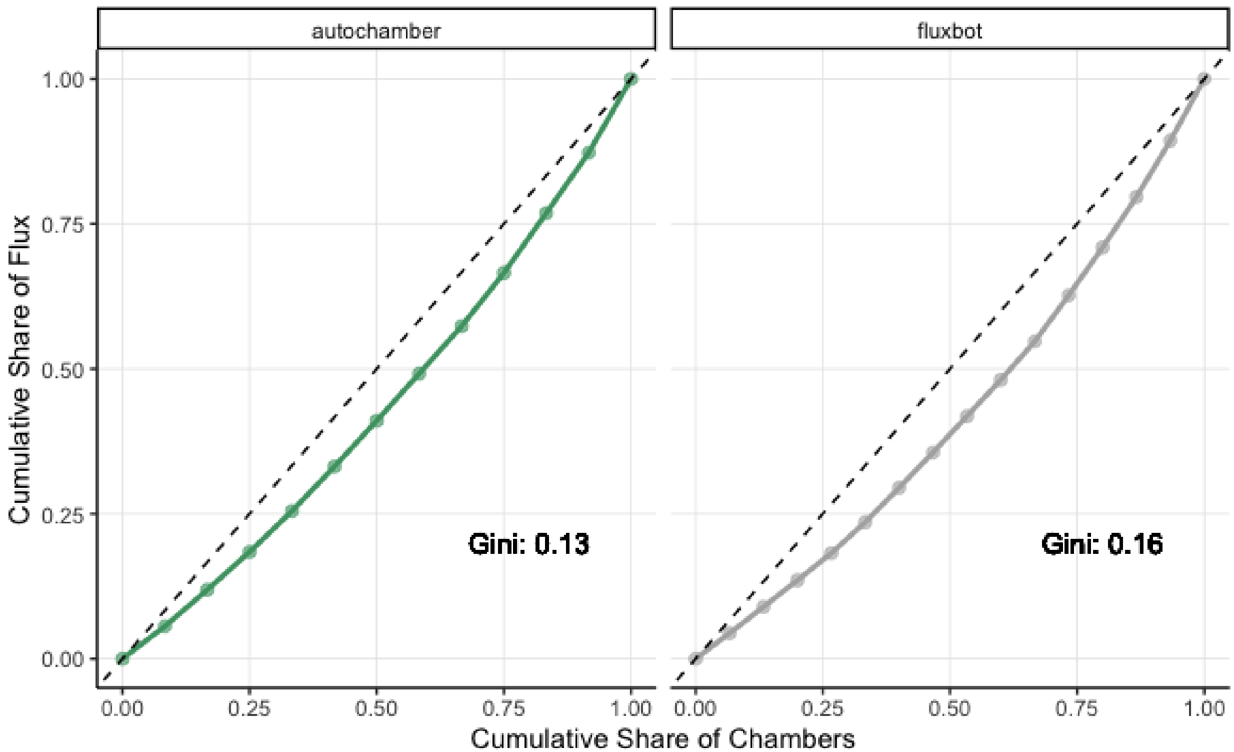

Fig. 8 | Lorenz curves for each array. Lorenz curves comparing flux inequality between two measurement methods (autochamber and fluxbot). The x-axis represents the cumulative share of sensors, and the y-axis represents the cumulative share of flux. The dashed diagonal line represents perfect equality, where each sensor contributes equally to the total flux. The deviation of each Lorenz curve from the diagonal line indicates the degree of inequality in flux distribution. The Gini coefficient, displayed on each plot, quantifies this inequality, with values closer to 1 indicating greater inequality.

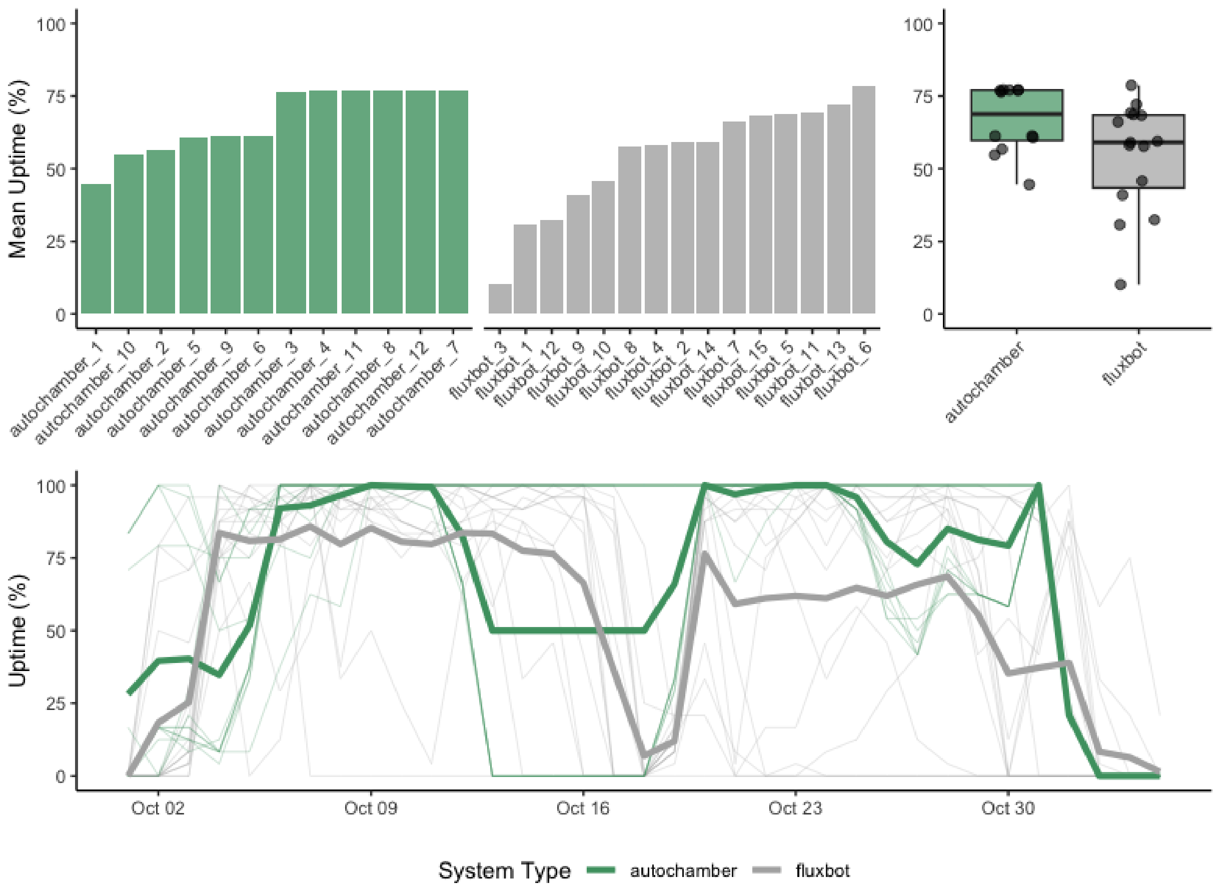

Fig. 9 | System uptime summary for autochamber and Fluxbot 2.0 arrays. Top panels: mean daily uptime for each unit (barplot, left) and distribution of mean uptime across units (boxplot, right) during the October 2024 deployment. Bottom panel: daily uptime time series, with thin lines showing individual unit performance and thick lines showing array-wide daily means. Both systems maintained high data retention (>95%) and captured consistent temporal patterns, with Fluxbot arrays demonstrating resilience to localized failures and autochambers achieving slightly higher overall data capture efficiency.

4. Discussion

4.1 System Performance and Measurement Validation

Our findings support the emerging literature that low-cost sensors provide a robust and cost-effective alternative to traditional autochamber systems for monitoring soil respiration (Harmon et al. 2015; D. Bastviken et al. 2015; E. Forbes et al. 2023). The high operational reliability (>95% uptime) and strong statistical agreement with autochambers (CCC = 0.70, $p = 0.185$)

suggest that Fluxbot 2.0 can effectively replicate the measurement quality of established systems while offering substantial advantages in terms of deployment flexibility and cost-effectiveness (Macagga et al. 2024; Al Hamwi et al. 2024). The precision of the Fluxbot sensors was sufficient to provide accurate flux estimates without the need for calibration to exact (“absolute”) gas concentration values. This is because the flux calculation depends on the rate of change in concentration over time, not on the absolute concentration level itself. In other words, even if the sensors have a small bias in their absolute readings, the slope of the concentration increase inside the closed chamber—on which flux estimates are based—remains reliable. The closed-chamber accumulation approach utilized by Fluxbots has been shown to maintain robust performance without frequent calibration (Brecheisen et al. 2019; Harmon et al. 2015).

From October 2-31, 2023, the Fluxbot array collected 6,824 flux measurements from 10,800 potential measurement intervals (63.2% collection rate), with 6,667 measurements retained after quality control (97.7% retention rate), yielding an overall success rate of 61.7%. The autochamber array collected 13,525 flux measurements from 17,280 potential measurements (78.3% collection rate), with 12,926 measurements retained after quality control (95.6% retention rate), yielding an overall success rate of 74.8%. Both systems demonstrated excellent data quality with retention rates exceeding 95%. This comprehensive dataset demonstrates the scalability of automated chamber approaches (Liang, Inoue, and Fujinuma 2003) while maintaining measurement quality across distributed arrays.

While the autochamber system achieved higher overall data collection efficiency, the system was more vulnerable to periods of complete shutdown. Because fluxbots are autonomous, the fluxbot array remained more resilient than the autochamber array; during times of lost power or pneumatic malfunctions, the entire autochamber array in a given location would fail, resulting in longer periods with no data collected whatsoever. System reliability over the 30-day deployment period revealed that the Fluxbot array maintained replicated plot-level coverage (defined as $\geq$3 units collecting data per plot per observation interval) 90.7% of the time in stand 1 and 80.4% of the time in stand 2; while autochambers maintained coverage only 70.6% of the time in stand 1, and 89.3% of the time in stand 2. Thus, the system offers trade-offs but some benefits for ensuring reliability in a distributed array, which could be beneficial particularly for monitoring efforts focused on comparing plots in different landscape or treatment conditions.

The moderate R^2 value (0.54) in direct comparisons between rolling average estimates of fluxes between the fluxbot and autochamber arrauys reflects the complex nature of soil CO_2 flux measurements. While perfect 1:1 correlation at fine temporal and spatial scales is not expected, emergent patterns at plot-level scales and in temporal responses show strong concordance between measurement systems. Microbial and root processes that drive soil respiration are both spatially and temporally dynamic, with multiple drivers regulating instantaneous flux at any given moment (Bradford and Ryan 2008; Vargas et al. 2011). This inherent variability manifests across scales, from sub-meter heterogeneity to landscape patterns (Martin and Bolstad 2009).

4.2 Temporal Resolution and Environmental Response

The clear and consistent diurnal patterns captured by both systems demonstrate the Fluxbots' capability to resolve fine-scale temporal dynamics in soil respiration. Both systems detected consistent diel flux patterns (fig. 6), with peak activity during midday hours reflecting the integration of temperature-dependent root respiration, microbial activity, and potential lagged responses to photosynthetic carbon allocation (Savage & Davidson, 2003; Tang et al., 2005) (table 1). These temporal patterns tracked well with soil temperature, demonstrating the importance of environmental drivers in shaping flux dynamics (Hollinger et al., 2004).

Table 2 | Summary statistics of soil CO_2 flux measurements during peak and minimum daily periods. Mean, median, 95th percentile, and standard error values for Fluxbot 2.0 and autochamber arrays during evening hours (15:00-20:00) and morning hours (05:00-10:00), corresponding to periods of maximum and minimum daily flux, respectively. Data are stratified by measurement system, time period, and forest stand to illustrate diurnal patterns and system performance across different site conditions during the October 2024 deployment period.

Summary Statistics: Flux by Array type, Location, and Approx. Min/Max Time of Day

			Summary Statistics				
Array	**Stand**	**Time of day**	**Mean**	**Median**	**95th Percentile**	**SE**	**N**
Autochamber array:							
autochamber	stand 1	evening	3.03	2.97	4.61	0.05	325
autochamber	stand 1	morning	2.81	2.77	4.60	0.05	368
autochamber	stand 2	evening	2.60	2.58	4.12	0.03	502
autochamber	stand 2	morning	2.30	2.22	3.36	0.03	468
Fluxbot array:							
fluxbot	stand 1	evening	2.66	2.56	4.68	0.05	458
fluxbot	stand 1	morning	2.27	2.04	4.41	0.05	409
fluxbot	stand 2	evening	2.70	2.60	4.65	0.06	407
fluxbot	stand 2	morning	2.39	2.26	4.49	0.06	389

Note:
SE = Standard Error
P95 = 95th Percentile
N = number of flux obs.
morning = 5am - 10am
evening = 3pm - 8pm

The temperature sensitivity of respiration, calculated as Q10, is a critical parameter in understanding soil carbon dynamics. Our observed Q10 values (2.31 for autochambers and 2.86

for Fluxbot 2.0) fall within the range commonly reported in the literature for temperate forest soils (typically 2.0 to 3.0) (Eric A. Davidson and Janssens 2006). The slightly higher Q10 value for Fluxbot 2.0 might reflect differences in chamber design affecting soil microclimate or variations in sensor response characteristics: specifically, a significantly smaller collar footprint resulting in a significantly smaller area measured. Seminal studies (Lloyd and Taylor 1994) have shown that Q10 values can vary significantly depending on soil type, moisture, and biological activity, reinforcing the importance of continuous, high-resolution measurements. Critically, both systems captured broader temporal trends, such as seasonal shifts in flux patterns. The ability to detect such trends is essential for understanding long-term ecosystem carbon dynamics and responses to environmental change (Jian et al. 2018).

4.3 Capturing Landscape Heterogeneity

Our GAM model found no significant differences in fluxes between the hemlock stands during our October deployment. While previous work at these sites has documented differences during peak growing season, the magnitude of these differences typically dissipates during shoulder seasons as both plant and microbial processes slow (Giasson et al. 2013; Phillips, Varner, and Frolking, n.d.). The lack of between-stand differences in our study period does not diminish the demonstrated capability of the Fluxbot 2.0 arrays to accurately reproduce site means and variability across distributed patches of a landscape, especially given the similar patterns captured by the autochamber array—rather, it reflects the seasonal context of our deployment.

One of the key strengths of the Fluxbot 2.0 system is its ability to capture spatial variability in soil respiration across multiple scales. At the local scale, Fluxbots captured heterogeneity driven by microtopography, soil composition, and vegetation patterns, as evidenced by the range of individual chamber medians spanning 1.5 to 4.0 µmol $m^{-2}s^{-1}$ (Figure 2). At the landscape scale, they successfully monitored broader patterns associated with forest stand conditions and environmental gradients, demonstrating equivalent performance to autochambers in characterizing site-level flux distributions. This capability provides both mechanistic insight into localized flux drivers and a broader perspective on regional carbon budgets (Rodeghiero and Cescatti 2008). The ability to capture multiscale variability is essential for accurate ecosystem carbon accounting and for understanding the spatial distribution of soil carbon flux hotspots. The Lorenz curve analysis, showing very similar Gini coefficients (0.13 for autochambers and 0.16 for Fluxbot 2.0 arrays), underscores the system's effectiveness in capturing flux heterogeneity with minimal deviation from established methods.

4.4 Improving carbon cycling estimates

Other methods that currently capture high spatial coverage and resolution of soil C fluxes include tower networks, satellites, and airborne eddy covariance systems. However, these approaches often lack the fine spatial resolution provided by distributed ground-based systems like Fluxbots. For example, eddy covariance towers provide high temporal resolution but are limited in spatial specificity, while satellite-based methods offer broad coverage but lower temporal and spatial resolution (Baldocchi 2003). Airborne eddy covariance systems can bridge some gaps but are logistically complex and costly. The concept of distributed sensor networks is not new and has been successfully applied in other fields, such as air quality monitoring for environmental and public health (Castell et al. 2017; Hasenfratz et al. 2015; Dubey et al. 2024). Low-cost air quality sensor networks have revolutionized the ability to track pollutants across urban areas, providing actionable data for policymakers and communities. Similarly, distributed Fluxbot arrays have the potential to democratize soil carbon monitoring, enabling broader participation and more comprehensive datasets for climate research.

The scalable deployment capabilities of Fluxbot 2.0 arrays extend beyond traditional carbon accounting to support emerging research areas and practical applications. In zoogeochemistry, distributed sensor networks can quantify how animal activities—from soil-dwelling invertebrates to large herbivores—create spatial patterns in biogeochemical cycling, enabling researchers to map animal-mediated carbon hotspots across landscapes. For agricultural monitoring, measurement, reporting, and verification (MMRV) protocols increasingly require high-resolution soil carbon data to validate carbon sequestration claims in regenerative farming and carbon credit programs, where Fluxbot arrays can provide the temporal and spatial resolution needed for robust verification. Additionally, these systems offer valuable applications in ecosystem restoration monitoring, where tracking soil respiration recovery can indicate restoration success, and in urban ecology, where understanding soil carbon dynamics in fragmented green spaces supports sustainable city planning. The autonomous design also makes Fluxbot arrays particularly suitable for monitoring remote or inaccessible ecosystems, filling critical data gaps in global carbon cycle research and supporting evidence-based environmental management decisions across diverse landscapes.

Our results demonstrate that distributed arrays of low-cost flux chambers can effectively monitor soil carbon dynamics across heterogeneous landscapes. The validated performance of distributed Fluxbot arrays has important implications for expanding carbon monitoring beyond intensively studied research sites. The relatively low cost and simplified deployment requirements make it feasible to establish monitoring networks across larger spatial extents and in previously understudied ecosystems, similar to how other low-cost sensor networks have democratized environmental monitoring (Harmon et al. 2015; Rundel et al. 2009; D. Bastviken et al. 2015).

The high temporal resolution of the measurements combined with extensive spatial coverage enables detection of both fine-scale patterns and broader ecosystem-level trends (David Bastviken et al. 2022). This capability opens new opportunities for studying soil carbon cycling across landscapes and improving geographical coverage of flux measurements (Jian et al. 2018). The demonstrated ability of Fluxbots to capture both fine-scale temporal patterns and spatial heterogeneity makes them particularly valuable for studies of ecosystem response to environmental change and for improving carbon accounting in managed systems, including nature-based climate solutions where comprehensive monitoring across diverse landscapes is essential (Novick et al. 2022).

4.5 Limitations and Future Directions

While our study demonstrates the utility of Fluxbots for monitoring soil respiration, future research should focus on long-term deployments across diverse ecosystems to further validate their performance under varying environmental conditions. Additionally, integrating Fluxbot data with other remote sensing and modeling approaches could provide more comprehensive insights into soil carbon dynamics at regional and global scales.

Exploring the potential of Fluxbots for measuring other greenhouse gases (e.g., CH_4, N_2O) and incorporating additional environmental sensors could further enhance their utility in ecosystem monitoring. Addressing challenges related to sensor calibration, data transmission, and long-term maintenance will also be critical for ensuring the sustained operation of distributed sensor networks.

4.6 Conclusions

This study demonstrates that arrays of low-cost, autonomous flux chambers can effectively monitor soil carbon dynamics at both fine spatial scales and across broader landscape extents. The strong agreement between Fluxbot and autochamber measurements validates this approach for capturing spatial and temporal patterns in soil respiration. The scalability and affordability of Fluxbots open new possibilities for studying soil carbon dynamics across spatial and temporal scales previously difficult to address. By enabling expanded deployment of flux monitoring networks (Pan et al. 2024; D. Bastviken et al. 2015), this technology can help advance our understanding of how ecosystem structure and function influence carbon cycling across heterogeneous landscapes. Ultimately, these systems can contribute to improving ecosystem model parameterization, global carbon monitoring efforts, and our understanding of ecosystem responses to environmental change.

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