

¹ **neonSoilFlux: An R Package for Continuous
2 Sensor-Based Estimation of Soil CO₂ Fluxes**

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²⁴ **Conflict of Interest Statements**

²⁵ None of the authors have a financial, personal, or professional conflict of interest related to
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³⁶ Writing – review and editing: John Zobitz, Naupaka Zimmerman, Zoey Werbin, Edward Ayres,
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³⁹ Project Administration: John Zobitz; Naupaka Zimmerman; Funding Acquisition: John Zob-
⁴⁰ itz; Naupaka Zimmerman

⁴¹ **Data Availability**

⁴² Anonymous field-collected data, `neonSoilFlux` calculated outputs, and manuscript-generating
⁴³ code for peer review are provided as supplemental files. An anonymous link for peer-review
⁴⁴ is here: <https://doi.org/10.5281/zenodo.1695117>. This will be made publicly available upon
⁴⁵ publication.

46 **1 Abstract**

- 47 1. Accurate quantification of soil carbon fluxes is essential to reduce uncertainty in esti-
48 mates of the terrestrial carbon sink. However, these fluxes vary over time and across
49 ecosystem types and so it can be difficult to estimate them accurately across large scales.
50 The flux gradient method estimates soil carbon fluxes using co-located measurements of
51 soil CO₂ concentration, soil temperature, soil moisture, and other soil properties. The
52 National Ecological Observatory Network (NEON) provides such data across 20 ecocli-
53 climatic domains spanning the continental U.S., Puerto Rico, Alaska, and Hawai‘i.
- 54 2. We present an R software package (`neonSoilFlux`) that acquires soil environmental data
55 to compute half-hourly soil carbon fluxes for each soil replicate plot at a given terrestrial
56 NEON site. To assess the computed fluxes, we visited six focal NEON sites and measured
57 soil carbon fluxes using a closed-dynamic chamber approach.
- 58 3. Outputs from the `neonSoilFlux` showed agreement with measured fluxes (R^2 between
59 measured and `neonSoilFlux` outputs ranging from 0.04 to 0.81 depending on calculation
60 method used); measured outputs generally fell within the range of calculated uncertain-
61 ties from the gradient method. Calculated fluxes from `neonSoilFlux` aggregated to the
62 daily scale exhibited expected site-specific seasonal patterns.
- 63 4. While the flux gradient method is broadly effective, its accuracy is highly sensitive to
64 site-specific inputs, including the extent to which gap-filling techniques are used to in-
65 terpolate missing sensor data and to estimates of soil diffusivity and moisture content.
66 Future refinement and validation of `neonSoilFlux` outputs can contribute to existing
67 databases of soil carbon flux measurements, providing near real-time estimates of a crit-
68 ical component of the terrestrial carbon cycle.

⁶⁹ **1.1 Keywords**

⁷⁰ Soil carbon, carbon dioxide, flux gradient, carbon cycle, field validation, soil respiration, ecosys-
⁷¹ tem variability, diffusion

⁷² **2 Data for peer review**

⁷³ Anonymous field-collected data, `neonSoilFlux` calculated outputs, and manuscript-generating
⁷⁴ code for peer review are provided as supplemental files. An anonymous link for peer-review
⁷⁵ is here: <https://doi.org/10.5281/zenodo.1695117>. This will be made publicly available upon
⁷⁶ publication.

⁷⁷ **3 Introduction**

⁷⁸ Soils contain the planet's largest reservoir of terrestrial carbon (Jobbágy & Jackson, 2000). A
⁷⁹ critical component of this reservoir is soil organic matter, the accumulation of which is influ-
⁸⁰ enced by biotic factors such as above-ground plant inputs (Jackson et al., 2017). These inputs
⁸¹ in turn are influenced by environmental factors such as growing season length, temperature,
⁸² and moisture (Desai et al., 2022), which also affect the breakdown of soil organic matter and its
⁸³ return to the atmosphere. Across heterogeneous terrestrial landscapes, the interplay between
⁸⁴ these biotic and abiotic factors influence the size of the soil contribution to the terrestrial
⁸⁵ carbon sink (Friedlingstein et al., 2025). However, the heterogeneity of these processes across
⁸⁶ diverse ecosystems in the context of rapid environmental change leads to large uncertainty
⁸⁷ about the magnitude of this sink in the future, and thus there remains a pressing need to
⁸⁸ quantify changes in soil carbon pools and fluxes across scales.

89 Ecological observation networks such as the United States' National Ecological Observatory
90 Network (NEON) and others (e.g. the globally-distributed FLUXNET or the European Inte-
91 grated Carbon Observation System) present a significant advancement in the nearly continuous
92 observation of biogeochemical processes at the continental scale. Notably, at 47 terrestrial sites
93 across the continental United States that span 20 ecoclimatic domains, NEON provides half-
94 hourly measurements of soil CO₂ concentration, temperature, and moisture at different vertical
95 depths. Each of these NEON sites also encompasses measurements of the cumulative sum of all
96 ecosystem carbon fluxes in an airshed using the eddy covariance technique (Baldocchi, 2014).
97 Soil observations provided by NEON are on the same timescale and standardized with eddy co-
98 variance measurements from FLUXNET. These types of nearly continuous observational data
99 (NEON and FLUXNET) can be used to reconcile differences between model-derived or data-
100 estimated components of ecosystem carbon flux (Jian et al., 2022; Luo et al., 2011; Phillips et
101 al., 2017; J. Shao et al., 2015; P. Shao et al., 2013; Sihl et al., 2016).

102 Estimated or observed soil carbon fluxes are a key metric for understanding change in soil
103 carbon pools over time (Bond-Lamberty et al., 2024). A soil carbon flux to the atmosphere
104 (F_S , units $\mu\text{mol m}^{-2} \text{ s}^{-1}$), represents the aggregate process of transfer of soil CO₂ to the
105 atmosphere from physical and biological processes (e.g. diffusion and respiration). Soil carbon
106 fluxes can be assumed to encompass soil carbon respiration from autotrophic or heterotrophic
107 sources (Davidson et al., 2006) and modeled with a exponential Q_{10} paradigm (Bond-Lamberty
108 et al., 2004; Chen & Tian, 2005; Hamdi et al., 2013).

109 One common method by which F_S is measured in the field is through the use of soil chambers
110 in a closed, well-mixed system (Norman et al., 1997) with headspace trace gas concentrations
111 measured with an infrared gas analyzer (IRGA). F_S can also be estimated from soil CO₂
112 measurements at different depths in the soil using the flux-gradient method (Maier & Schack-
113 Kirchner, 2014). Closed-chamber IRGA measurements, while being the most common method,

require either frequent in-person site visits or expensive and fragile automated systems. The potential of the gradient method is that fluxes can be estimated from continuous data recorded by robust solid-state sensors. The flux-gradient method is an approach that uses conservation of mass to calculate flux at a vertical soil depth z at steady state by applying Fick's law of diffusion. A simplifying assumption for the flux-gradient method is that there is no mass transfer in the other spatial dimensions x and y (Maier & Schack-Kirchner, 2014). The diffusivity profile, a key component of this calculation, varies across the soil depth as a function of soil temperature, soil volumetric water content, atmospheric air pressure, and soil bulk density (Millington & Shearer, 1971; Moldrup et al., 1999; Sallam et al., 1984).

Databases such as the Soil Respiration Database (SRDB) or the Continuous Soil Respiration Database (COSORE) add to the growing network of resources for making collected observations of soil fluxes available to other researchers (Bond-Lamberty, 2018; Bond-Lamberty et al., 2020; Bond-Lamberty & Thomson, 2010; Jian et al., 2021; Jiang et al., 2024). However, these databases currently encompass primarily direct soil measurements of fluxes (i.e. those using methods like the closed-chamber method described above). Currently, NEON provides all measurements to calculate F_S from Fick's law, but soil flux as a derived data product was descoped from the initial network launch due to budget constraints (Berenbaum et al., 2015). Deriving estimates of F_S using continuous sensor data across NEON sites using NEON data thus remains a high priority.

This study describes an R software package, `neonSoilFlux`, that computes a standardized estimate of F_S at all terrestrial NEON sites using the flux-gradient method. Using direct chamber-based field observations of soil carbon dioxide flux from a subset of terrestrial NEON sites spanning six states, we provide a direct validation of F_S from `neonSoilFlux`. While open source R software tools currently exist for processing chamber-based flux measurements (Jurasinski et al., 2022; Pedersen, 2024; Rheault et al., 2024; Wilson et al., 2024; Zhao, 2019),

¹³⁹ to our knowledge this is the first package that incorporates NEON data directly.

¹⁴⁰ Key objectives of this study are to:

- ¹⁴¹ 1. Apply the flux-gradient method to estimate soil CO₂ flux from continuous sensor mea-
- ¹⁴² surements across six NEON sites.
- ¹⁴³ 2. Benchmark estimated soil carbon fluxes against field measurements (e.g. direct chamber
- ¹⁴⁴ measurements of soil flux).
- ¹⁴⁵ 3. Identify sources of error in the flux-gradient approach across diverse sites in order to
- ¹⁴⁶ guide future work.

¹⁴⁷ **4 Materials and Methods**

¹⁴⁸ **4.1 Field methods**

¹⁴⁹ **4.1.1 Focal NEON Sites**

¹⁵⁰ In order to acquire field data to validate model predictions of flux, we selected six terrestrial
¹⁵¹ NEON sites for analysis. We conducted roughly week-long field measurement campaigns at
¹⁵² these sites, which span a range of environmental gradients and terrestrial domains (Table 1).
¹⁵³ SJER, SRER, and WREF were visited during May and June of 2022, and WOOD, KONZ,
¹⁵⁴ and UNDE during May and June of 2024.

¹⁵⁵ **4.1.2 Soil collar placement**

¹⁵⁶ Either one (2022 sampling campaign) or two (2024 sampling campaign) PVC soil collars (20.1
¹⁵⁷ cm inside diameter) were installed in close proximity to the permanent NEON soil sensors at

158 each site (Figure 1). As instruments in the NEON soil sensor arrays can occasionally break
159 down or stop working, the specific soil plot where we made measurements was chosen at each
160 site in consultation with NEON staff to maximize likelihood of quality soil sensor measurements
161 during the duration of the IRGA measurements. The plot selected at each site (out of the 5 in
162 each replicate array at each site) are presented in the last column of Table 1. After installation,
163 collar(s) were left to equilibrate for approximately 24 hours prior to any measurements being
164 taken.

165 **4.1.3 Infrared gas analyzer measurements of soil CO₂ flux**

166 In 2022, we then made measurements of flux on an hourly interval for 8 hours each day.
167 Measurements were taken from roughly 8 am to 4 pm, with the time interval selected to
168 capture the majority of the diurnal gradient of soil temperature each day. These measurements
169 were made using a LI-6800 infrared gas analyzer instrument (LI-COR Environmental, Lincoln,
170 NE) fitted with a soil chamber attachment (attachment 6800-09). In 2024, we again used the
171 same LI-6800 instrument, but made half-hourly measurements over an approximately 8 hour
172 period. In addition, in 2024 we also installed a second collar and used a second instrument, an
173 LI-870 CO₂ IRGA, connected to an automated robotic chamber (LI-COR chamber 8200-104)
174 controlled by an LI-8250 multiplexer to make automated measurements. The multiplexer was
175 configured to take half-hourly measurements 24 hours a day for the duration of our sampling
176 bout at each site. Each instrument was paired with a soil temperature and moisture probe
177 (Stevens HydraProbe, Stevens Water, Portland, OR) that was used to make soil temperature
178 and moisture measurements concurrent with the CO₂ flux measurements. Chamber volumes
179 were set by measuring collar offsets at each site. System checks were conducted daily for the
180 LI-6800 and weekly for the LI-8250. Instruments were factory calibrated before each field
181 season.

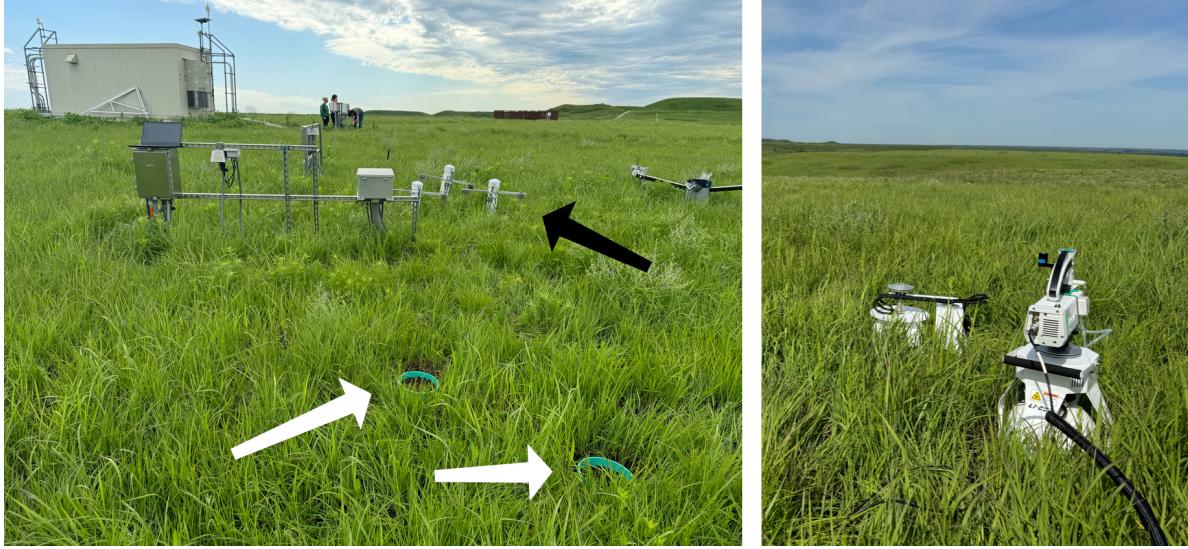


Figure 1: Spatial layout of field sampling using a closed-dynamic chamber setup at a representative NEON site (KONZ). Left image shows collars (white arrows) and permanent soil sensor installation (black arrow) and right image shows the LI-6800 (foreground) and LI-8200-104 (background) instruments placed on the collars.

Table 1: Listing of NEON sites studied for field work and analysis. Site refers to NEON site codes: Santa Rita Experimental Range (SRER), San Joaquin Experimental Range (SJER), Wind River Experimental Forest (WREF), Chase Lake National Wildlife Refuge (WOOD), Konza Prairie Biological Station (KONZ), and the University of Notre Dame Environmental Research Center (UNDE). Location is reported in decimal degrees of latitude and longitude. Other abbreviations include Mean Annual Temperature (MAT); \bar{T}_S : average soil temperature during field measurements; \bar{SWC} : average soil water content during field measurements. Dates refer to field measurement dates for each site. Plot refers to the particular location in the soil sensor array (denoted as HOR by NEON) where field measurements were made.

Site	Location	Ecosystem	MAT	\bar{T}_S	MAP	\bar{SWC}	Dates	Plot
SRER	31.91068, -110.83549	Shrubland	19.3 °C	47.6 °C	346 mm	4.0%	May 29– June 1 2022	004
SJER	37.10878, -119.73228	Oak woodland	16.4 °C	41.7 °C	540 mm	1.2%	June 1–4 2022	005
WREF	45.82049, -121.95191	Evergreen forest	9.2 °C	15.3 °C	2225 mm	27.2%	June 7–9 2022	001
WOOD	47.1282, -99.241334	Restored prairie	4.9 °C	14.9 °C	495 mm	14.9%	June 3–9 2024	001
KONZ	39.100774, -96.563075	Tallgrass prairie	12.4 °C	23.4 °C	870 mm	23.4%	May 29– June 1 2024	001

Table 1: Listing of NEON sites studied for field work and analysis. Site refers to NEON site codes: Santa Rita Experimental Range (SRER), San Joaquin Experimental Range (SJER), Wind River Experimental Forest (WREF), Chase Lake National Wildlife Refuge (WOOD), Konza Prairie Biological Station (KONZ), and the University of Notre Dame Environmental Research Center (UNDE). Location is reported in decimal degrees of latitude and longitude. Other abbreviations include Mean Annual Temperature (MAT); \bar{T}_S : average soil temperature during field measurements; \bar{SWC} : average soil water content during field measurements. Dates refer to field measurement dates for each site. Plot refers to the particular location in the soil sensor array (denoted as HOR by NEON) where field measurements were made.

Site	Location	Ecosystem	MAT	\bar{T}_S	MAP	\bar{SWC}	Dates	Plot
UNDE	46.23391, -89.537254	Deciduous forest	4.3 °C	13.0 °C	802 mm	13.0%	May 22–25 2024	004

182 4.1.4 Post-collection processing of field data

183 We used LI-COR SoilFluxPro software (v 5.3.1) to assess the data after collection and to inform
 184 sampling parameters. We checked appropriateness of dead band and measurement durations
 185 using built-in evaluation tools. Based on this, the deadband period was set for 30-40 seconds,
 186 depending on the site, and the measurement duration was 180 seconds with a 30 second pre-
 187 purge and a 30 second post-purge at most sites, and a 90 second pre- and post-purge at sites
 188 with higher humidity due to recent precipitation events. We also assessed the R^2 of linear and
 189 exponential model fits to measured CO₂ to verify measurement quality.

190 4.2 neonSoilFlux R package

191 We developed an R package called `neonSoilFlux` (Zobitz et al., 2024) to compute half-hourly
 192 soil carbon fluxes and uncertainties from NEON data. The objective of the `neonSoilFlux`
 193 package is a unified workflow (Figure 2) for soil data acquisition and analysis that supplements
 194 the existing `neonUtilities` data acquisition R package (Lunch et al., 2025).

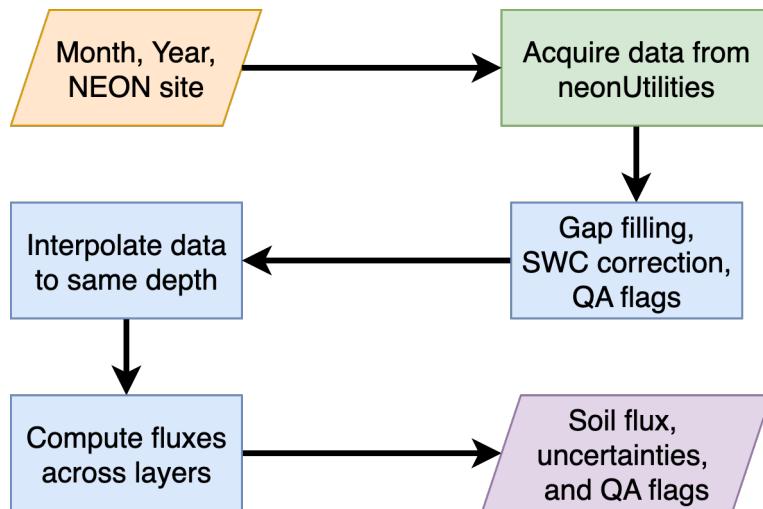


Figure 2: Diagram of `neonSoilFlux` R package. For a given month, year, and NEON site (orange parallelogram), the package acquires all relevant data to compute F_S using the `neonUtilities` R package (green rectangle). Data are gap-filled according to reported QA flags and adjusted for changes in soil water content (SWC) calibration coefficients, then interpolated to the same measurement depth before computing the soil flux, uncertainties, and final QA flags (blue rectangles). The package reports the associated soil flux, uncertainties, and quality assurance (QA) flags for the user (purple parallelogram).

At a given NEON site there are five replicate soil plots, each with measurements of soil CO_2 concentration, soil temperature, and soil moisture at different depths (Figure 3). The `neonSoilFlux` package acquires measured soil CO_2 concentration (NEON, 2024b), soil temperature (NEON, 2024d), soil water content (NEON, 2024e), barometric pressure from the nearby tower (NEON, 2024a), and soil properties (e.g. bulk density) (NEON, 2024c) from a range of different NEON data products. The static soil properties were collected by NEON staff from a nearby soil pit during initial site characterization and are assumed to be constant at each site. A soil flux calculation is computed at each replicate soil plot.

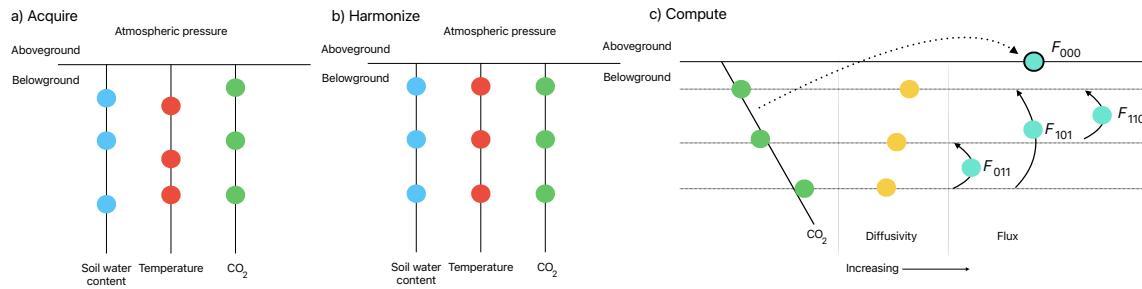


Figure 3: Model diagram of the data workflow for the `neonSoilFlux` R package. a) Acquire: Data are obtained for a given NEON location and horizontal sensor location, which includes soil water content, soil temperature, CO_2 concentration, and atmospheric pressure. All data are screened for quality assurance; if gap-filling of missing data occurs, it is flagged for the user. b) Harmonize: Any belowground data are then harmonized to the same depth as CO_2 concentrations using linear regression. c) Compute: The flux across a given depth is computed via Fick's law, denoted with F_{ijk} , where i , j , or k are either 0 or 1 denoting the layers the flux is computed across ($i = \text{closest to surface}$, $k = \text{deepest}$). F_{000} represents a flux estimate where the gradient $d\text{C}/dz$ is the slope of a linear regression of CO_2 with depth.

The workflow to compute a value of F_S with `neonSoilFlux` consists of three primary steps, illustrated in Figure 3. First, NEON data are acquired for a given site and month via the `neonUtilities` R package (yellow parallelogram and green rectangle in Figure 2 and Panel a in Figure 3). Acquired environmental data can be exported to a comma separated value file for additional analysis. Quality assurance (QA) flags are reported as an indicator variable. Since

208 the calibration coefficients on the soil water content sensors have changed over time (NEON,
209 2024e), raw sensor measurements were back-calculated and soil-specific calibrations were ap-
210 plied following Ayres et al. (2024) to generate a consistent time series at each measurement
211 location.

212 The second step is harmonizing the data to compute soil fluxes across soil layers. This step
213 consists of three different actions (blue rectangles in Figure 2 and Panel b in Figure 3). If a
214 given observation by NEON is reported as not passing a quality assurance check, we applied
215 a gap filling method to replace that measurement with its monthly mean at that same depth
216 (Section 4.2.1). Belowground measurements of soil water and soil temperature are then inter-
217 polated to the same depth as soil CO₂ measurements. The diffusivity (Section 4.2.2) and soil
218 flux across different soil layers (Section 4.2.3) are then computed.

219 The third and final step is computing a surface soil flux through extrapolation to the sur-
220 face (purple parallelogram in Figure 2 and Panel c in Figure 3). Uncertainty on a soil flux
221 measurement is computed through quadrature. An aggregate quality assurance (QA) flag
222 for each environmental measurement is also reported, representing if any gap-filled measure-
223 ments were used in the computation of a soil flux. Within the soil flux-gradient method,
224 several different approaches can be used to derive a surface flux (Maier & Schack-Kirchner,
225 2014); the `neonSoilFlux` package reports four different possible values for soil surface flux
226 (Section 4.2.3) for each of two different methods of diffusivity estimation, for a total of eight
227 estimates of flux.

228 **4.2.1 Gap-filling routine**

229 NEON reports QA flags as binary values for each measurement and half-hourly interval. For
230 a given half-hour, if any input variable (soil CO₂ concentration, soil temperature, or soil

moisture) at depth z is flagged, computation of F_S is not possible. To address this, flagged measurements and their uncertainties were replaced with a bootstrapped monthly mean (\bar{m}) and monthly standard deviation (\bar{s}) (Efron & Tibshirani, 1994).

For each month, depth z , and variable, we computed bootstrapped estimates of \bar{m} and \bar{s} from the vectors of unflagged measurements (\mathbf{m}), reported standard errors (σ), and the 95% confidence interval (ϵ , or expanded uncertainty; Farrance & Frenkel (2012)). We also defined a bias vector $\mathbf{b} = \sqrt{\epsilon^2 - \sigma^2}$, which quantifies the spread of uncertainty in a given period and is incorporated into \bar{m} .

From these, 5000 bootstrap samples were generated for \mathbf{m}, σ , and \mathbf{b} . For each sample (m_k, b_k, σ_k) , we generated a vector \mathbf{n} (length $N = 5000$) by drawing from a normal distribution with mean $m_k + b_k$ and standard deviation σ_k . The sample mean and standard deviation were then computed from \mathbf{n} . The resulting distributions of sample means and sample standard deviations provided the bootstrapped monthly mean (\bar{m}) and standard error (\bar{s}) respectively.

This gap-filling procedure provides a consistent treatment across all data streams. However, alternative approaches may be better suited for longer gaps (e.g., correlations with other NEON measurement levels or soil plots) or for variable-specific conditions. We discuss the effect of gap-filling on our results in Section 6.1.

4.2.2 Soil diffusivity

Soil diffusivity D_a at a given measurement depth is the product of the diffusivity in free air $D_{a,0}$ ($\text{m}^2 \text{ s}^{-1}$) and the tortuosity ξ (no units) (Millington & Shearer, 1971).

We compute $D_{a,0}$ with Equation 1:

$$D_{a,0} = 0.0000147 \cdot \left(\frac{T_i + 273.15}{293.15} \right)^{1.75} \cdot \left(\frac{P}{101.3} \right) \quad (1)$$

253 where T_i is soil temperature ($^{\circ}\text{C}$) at depth i (NEON, 2024d) and P surface barometric pressure
 254 (kPa) (NEON, 2024a).

255 Previous studies by Sallam et al. (1984) and Tang et al. (2003) demonstrated the sensitivity
 256 of modeled F_S depending on the tortuosity model (ξ) used to compute diffusivity. At low
 257 soil water content, the choice of tortuosity model can lead to order-of-magnitude differences
 258 in D_a , which in turn affect modeled F_S . The `neonSoilFlux` package currently includes two
 259 approaches to calculate ξ , representing the range of tortuosity behavior reported in Sallam et
 260 al. (1984).

261 The first approach is the Millington-Quirk model (Millington & Shearer, 1971), in which
 262 tortuosity depends on both porosity and soil water content:

$$\xi = \frac{(\phi - SWC_i)^{10/3}}{\phi^2} \quad (2)$$

263 In Equation 2, SWC is the soil water content at depth i (NEON, 2024e) and ϕ is the porosity,
 264 which in turn is a function of soil physical properties (NEON, 2024c):

$$\phi = \left(1 - \frac{\rho_s}{\rho_m} \right) (1 - f_V) \quad (3)$$

265 In Equation 3, ρ_m is the particle density of mineral soil (2.65 g cm^{-3}), ρ_s the soil bulk density (g
 266 cm^{-3}) excluding coarse fragments greater than 2 mm (NEON, 2024c), and f_V is a site-specific
 267 value that accounts for the proportion of soil fragments between 2-20 mm. Soil fragments

268 greater than 20 mm were not estimated due to limitations in the amount of soil that can be
269 analyzed (NEON, 2024c). We assume that rock fragments contain no internal pores.

270 The Millington-Quirk model assumes ξ is modulated by the amount of fluid saturation in
271 soil pores (Millington & Shearer, 1971). In contrast, the Marshall model (Marshall, 1959)
272 expresses tortuosity as only a function of porosity ($\xi = \phi^{1.5}$), with ϕ defined from Equation
273 3. The Marshall model is independent of soil water content and assumes tortuosity is only
274 governed by soil structure. The `neonSoilFlux` package allows users to choose the tortuosity
275 model most appropriate for site-specific conditions and research goals.

276 **4.2.3 Soil flux computation**

277 We applied Fick's law (Equation 4) to compute the soil flux F_{ij} ($\mu\text{mol m}^{-2} \text{s}^{-1}$) across two
278 soil depths i and j :

$$F_{ij} = -D_a \frac{dC}{dz} \quad (4)$$

279 where D_a is the diffusivity ($\text{m}^2 \text{s}^{-1}$) and $\frac{dC}{dz}$ is the gradient of CO₂ molar concentration
280 ($\mu\text{mol m}^{-3}$, so the gradient has units of $\mu\text{mol m}^{-3} \text{m}^{-1}$). The soil surface flux is theoretically
281 defined by applying Equation 4 to measurements collected at the soil surface and directly
282 below the surface. Measurements of soil temperature, soil water content, and soil CO₂ molar
283 concentration across the soil profile allow for application of Equation 4 across different soil
284 depths. Each site had three measurement layers, so we denote the flux as a three-digit subscript
285 F_{ijk} with indicator variables i , j , and k indicate if a given layer was used (written in order of
286 increasing depth), according to the following:

- F_{000} is a surface flux estimate using the intercept of the linear regression of D_a with depth and the slope from the linear regression of CO₂ with depth (which represents $\frac{dC}{dz}$ in Fick's Law). Tang et al. (2003) used this approach to compute fluxes in an oak-grass savannah.
- F_{110} is a flux estimate across the two shallowest measurement layers.
- F_{011} is a flux estimate across the two deepest measurement layers.
- F_{101} is a flux estimate across the shallowest and deepest measurement layers.

For F_{110} , F_{011} , and F_{101} , the diffusivity used in Fick's Law is always at the deeper measurement layer. When used as a surface flux estimate we assume CO₂ remains constant above this flux depth. Uncertainty in all F_{ijk} values was quantified using quadrature (Taylor, 2022). These computed fluxes could provide the basis for additional soil flux estimates. For example, Tang et al. (2005) estimated surface flux by linearly extrapolating F_{110} and F_{011} to the soil surface.

4.3 Post processing evaluation

Following collection of field measurements and calculation of the soil fluxes from `neonSoilFlux` package, we compared measured F_S based on closed-dynamic chamber measurements with the LI-COR instruments to a given soil flux calculation from `neonSoilFlux` for each site and flux computation method and quantified the relationship statistically (R^2). Finally, for a half-hourly interval we also computed a *post hoc* diffusivity (D_a) using the LI-COR flux along with the CO₂ surface gradient reported by NEON using the measurement levels closest to the surface.

Table 2: Summary of measured soil characteristics and flux results from field measurements across six NEON sites using a LI-COR 6800 (LI-870/8250 measurements omitted to enable direct comparability) via the closed-dynamic chamber method. Numeric values for soil CO₂ flux, soil temperature, and volumetric soil water content (VSWC) are the mean and standard deviation of field measurements at each site.

Site	Flux μmol m ⁻² s ⁻¹	Soil temp °C	VSWC cm ³ cm ⁻³	n
UNDE	2.55 ± 0.26	14.33 ± 0.77	0.33 ± 0.02	61
WOOD	3.02 ± 0.4	16.01 ± 1.54	0.28 ± 0.01	53
WREF	3.62 ± 0.3	15.34 ± 1.76	0.27 ± 0.06	21
KONZ	6.35 ± 0.97	27.28 ± 4.14	0.37 ± 0.01	44
SJER	0.94 ± 0.02	41.68 ± 11.22	0.01 ± 0.01	32
SRER	0.72 ± 0.09	47.64 ± 7.46	0.04 ± 0.01	32

5 Results

Concordance between modelled and measured soil CO₂ flux

The sites we visited ranged substantially in both their annual average temperature and precipitation as well as their biome type (Table 2). These differences also influenced the wide range of observed flux rates across sites.

The timeseries of the measured fluxes from the LI-COR 6800 and 870/8250 were compared to modeled soil fluxes from the `neonSoilFlux` R package (Figure 4). We also assessed year-long estimated flux time series and compared those to field measurements made at each site (Figure 5). Results are reported in local time. Where applicable, sites are displayed from left to right by increasing soil temperature (Table 1). Positive values of the flux indicate that there is a flux moving towards the surface. Overall, with the exception of SRER (discussed later) the computed fluxes determined using a variety of plausible methods spanned the field-measured fluxes, but the specific flux-gradient method that best approximated field measurements varied by site.

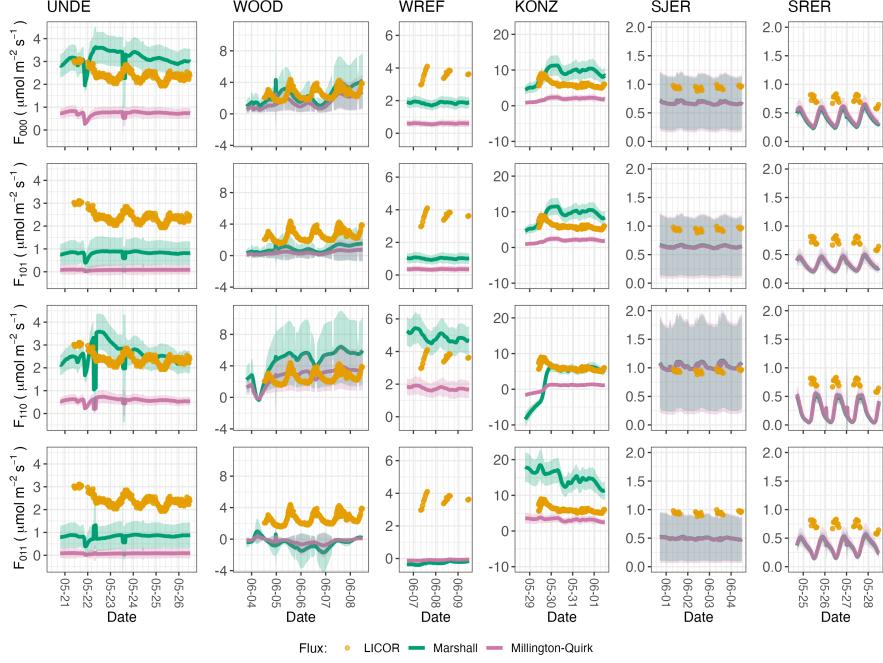


Figure 4: Timeseries of soil surface flux (F_S) from field-measured (yellow lines) and modeled soil fluxes (green or purple lines) by the `neonSoilFlux` R package. Fluxes from the `neonSoilFlux` R package are separated by the diffusivity model used (Millington-Quirk or Marshall, Section 4.2.2). Individual vertical axis labels in the first column represent the measurement levels where the flux-gradient approach is applied (Section 4.2.3). Ribbons for modeled soil fluxes represent ± 1 standard deviation. Results are reported in local time. WREF, SJER, and SRER were sampled in 2022, and UNDE, WOOD, and KONZ were sampled in 2024. Sites (columns) are arranged from left to right in terms of increasing mean annual temperature.

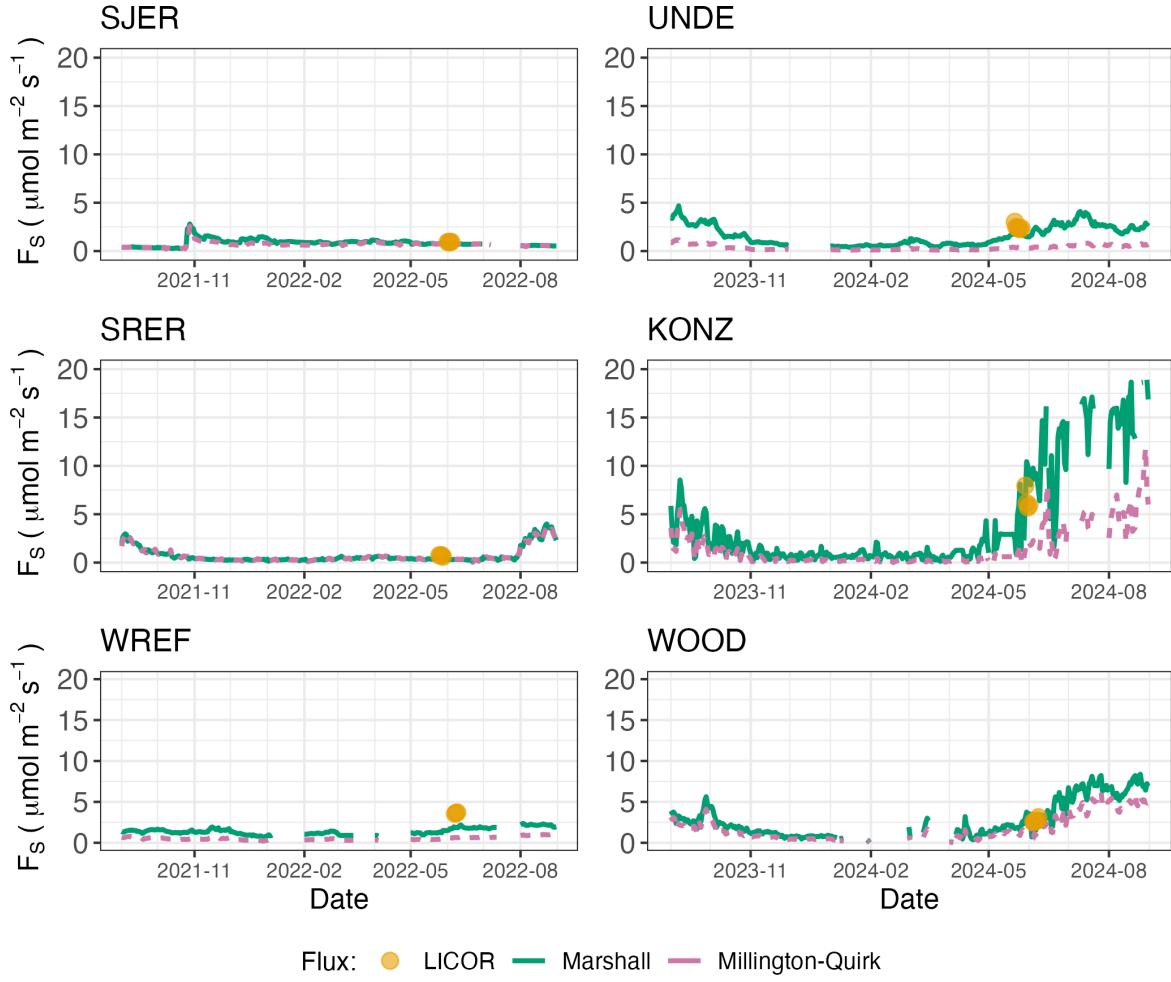


Figure 5: Timeseries of both daily-averaged field F_S (yellow circles) and daily ensemble averaged soil fluxes (average of F_{000} , F_{101} , F_{011} , F_{110} , Section 4.2.3) by the `neonSoilFlux` R package, separated by the diffusivity model used (green or purple lines, Millington-Quirk or Marshall, Section 4.2.2).

321 We calculated a statistical relationship between the various estimates of soil flux computed by
322 `neonSoilFlux` and the field-measured fluxes within daily interval periods. Statistics for these
323 comparisons are reported in Figure 6, which also shows how these fall relative to a 1:1 line.

324 **5.2 Effects of method choice on diffusivity estimates**

325 In four of six field sites, the *post hoc* D_a estimate fell roughly between the two diffusion
326 estimation methods; however this was less the case in the two driest sites, SJER and SRER
327 (Table 1), where the field estimate of diffusivity was either lower or higher than both of the
328 other methods (Figure 7).

329 **6 Discussion**

330 This study presents a unified data science workflow to efficiently process automated measure-
331 ments of belowground soil CO₂ concentrations, soil water content, and soil temperature to
332 infer estimates of soil surface CO₂ effluxes through application of Fick's Law (Equation 4).
333 Our core goals in this study were: (1) to generate estimates of soil flux from continuous soil
334 sensor data at terrestrial NEON sites using the flux-gradient method and then (2) to compare
335 those estimates to field-measured fluxes based on the closed chamber approach at six NEON
336 focal sites. We discuss our progress toward these core goals through (1) an overall evaluation
337 of the flux-gradient approach (and uncertainty calculation) and (2) site-specific evaluation of
338 differences in estimated vs measured fluxes.

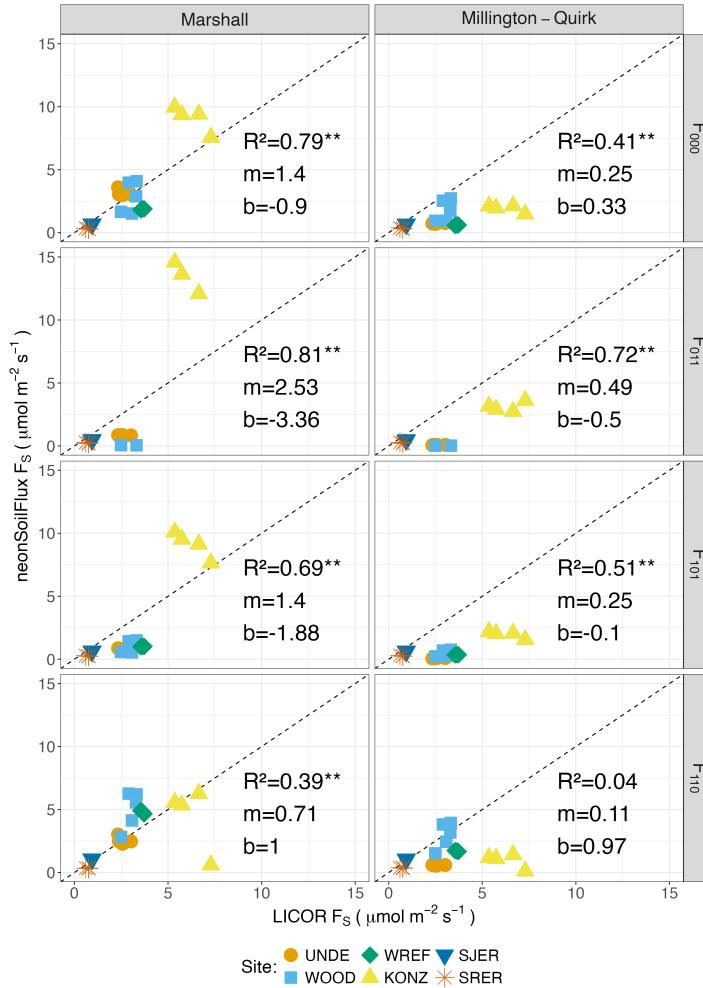


Figure 6: Statistical comparison between measured fluxes at each NEON site with fluxes reported by `neonSoilFlux` with the different flux calculation approaches and diffusivity calculations applied. Points are daily averages and LICOR F_S values are from the 6800 instrument only, for consistency. The dotted line represents a 1:1 relationship, and the reported R^2 quantifies the relationship between field-measured and `neonSoilFlux` estimated fluxes. * = significance at the 5% level, ** = significance at the 1% level. The slope (m) and intercept (b) of the linear regression between measured and modeled fluxes are also reported. The low-value outlier from KONZ in the F_{110} Marshall plot is an example of the effect of inverted CO₂ gradients causing an estimated flux to be negative, bringing down the daily mean, which later resolved as the soils dried back out.

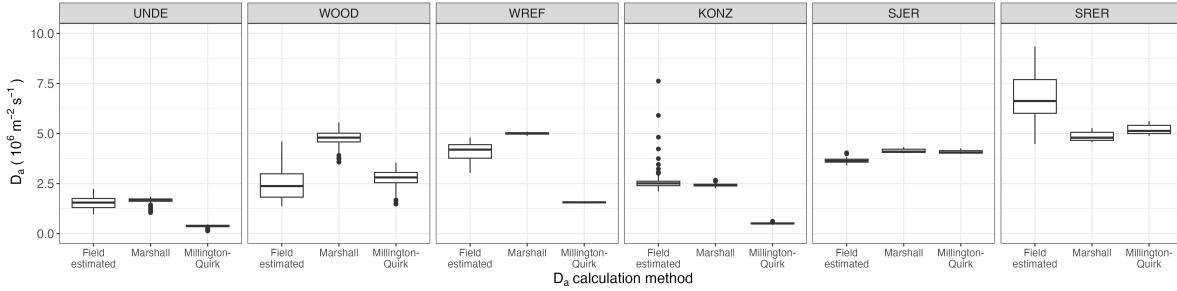


Figure 7: Distribution of diffusivity (D_a) at each study site. Values of D_a were provided by the `neonSoilFlux` package, computed from the Millington-Quirk or Marshall models (Section 4.2.2). A post-hoc estimate of diffusivity (labeled as “Field estimated”) was computed through the field measured flux (Figure 4), divided by the CO_2 gradient from the measurement levels closest to the soil surface, as reported by NEON. We only used F_S measured by the LICOR 6800 at all sites to standardize comparisons.

6.1 General evaluation of flux-gradient approach

Key assumptions of the flux-gradient approach are that CO_2 concentrations increase throughout the soil profile such that the highest concentrations are observed in the deepest layers. Additionally, field flux measurements should correlate with F_{000} because they represent surface fluxes. Periods where this gradient condition are not met generally are connected to processes that occur during soil wetting events, where more shallow soil layers produce higher concentrations of CO_2 due to microbial respiration pulses following rewetting. This effect is likely to be largest at sites with rich organic soils (e.g. KONZ). Based on this reasoning, in these types of situations we would *a priori* expect F_{011} (deepest layers) $\leq F_{101} \leq F_{110}$ (shallow layers) $\leq F_{000}$ (all layers) because the previous flux estimates rely primarily on CO_2 concentrations at deeper depths, and could miss high concentrations of CO_2 produced in shallower layers.

When modeling soil respiration, typically a non-linear response function that also considers soil type is used (Bouma & Bryla, 2000; Yan et al., 2016, 2018). For the `neonSoilFlux` package, soil type is connected to the measurement of bulk density, which was characterized at each NEON site. This bulk density estimate is based on replicate samples collected from the site

354 megapit at a subset of soil horizons, with an estimated uncertainty of $\pm 5\%$ (NEON, 2024c).
355 Coarse fragment estimates also have very large uncertainties, but because the volume fraction
356 tends to be low in surface soils it is unlikely to contribute much additional flux uncertainty.

357 Our results suggest that the most important way to improve reliability of the flux estimate is
358 to reduce the usage of gap-filled data. The current approach to gap filling in `neonSoilFlux`
359 uses monthly mean data to gap fill—this approach decreases the ability of the estimate to be
360 responsive to short-term pulses that occur with rapid weather shifts. Four sites (KONZ, SRER,
361 WREF, and UNDE) had more than 75% of half-hourly periods with no-gap filled measurements
362 (Figure S1, Supplementary Information). Two sites (SJER and WOOD) had more than 75%
363 of half-hourly intervals with just one gap-filled measurement. The large uncertainty evident
364 in Figure 4 for estimates from WOOD and SJER are thus due in part to the gap-filling used
365 in these sites (Figure S1). While we did not need to use gap-filled measurements to compute
366 the flux at WREF, field data collection occurred following a severe rainstorm, with soils at the
367 beginning of the sampling week near their water holding capacity. In general, we recommend
368 that whenever possible, knowledge of local field conditions should influence analysis decisions
369 in addition to any QA filtering protocols in the `neonSoilFlux` package.

370 We recognize that this gap-filling approach may lead to gap-filled values that are quite different
371 from the actual values, such as an underestimate of soil moisture following rain events. Further
372 extensions of the gap filling method could use more sophisticated gap-filling routines, similar to
373 what is used for net ecosystem carbon exchange (Falge et al., 2001; Liu et al., 2023; Mariethoz et
374 al., 2015; Moffat et al., 2007; Zhang et al., 2023). Additionally, since the deepest temperature
375 and soil moisture sensors are located below the deepest CO₂ sensors at NEON sites, it is
376 possible that excluding these deeper layers from consideration prior to analysis would lead to
377 a reduced need for gap filling. Future iterations of the `neonSoilFlux` package may incorporate
378 this as an option. The current gap-filling routine provides a consistent approach that can be

379 applied to each data stream, but further work may explore alternative gap-filling approaches.

380 6.2 Evaluation of flux-gradient approach at each site

381 Derived results from the `neonSoilFlux` package have patterns that are broadly consistent with
382 those directly measured in the field (Figure 4 and Figure 5), even though statistical comparisons
383 between the field-measured and `neonSoilFlux` values were quite variable (e.g. R^2 ranging
384 from 0.04 to 0.81; Figure 6). One advantage of the `neonSoilFlux` package is its ability to
385 calculate fluxes across different soil depths (Figure 3), which allows for additional site-specific
386 customization. We believe the package can provide a useful baseline estimate of soil fluxes
387 that can always be complemented through additional field measurements.

388 The six locations studied provide a range of case studies that suggest different considerations
389 may apply to different sites when applying the flux-gradient method. For example, the Santa
390 Rita Experimental Range (SRER) is a desert site characterized by sandy soil, which also was
391 the location of the highest field soil temperatures that we observed (Table 2). At SRER the
392 flux across the top two layers (F_{110}) produced a pattern of soil flux most consistent with the
393 observed field data. The remaining methods F_{101} , F_{011} , or F_{000} are derived from information
394 taken from the deepest layer, which seems to have been decoupled from the surface layers both
395 in terms of temperature and CO₂ concentration. This may be a general circumstance where
396 there are large diurnal temperature extremes that rapidly change during the course of a day
397 and overnight, leading to lags in the timing of when temperature increases propagate down to
398 deeper soil layers.

399 Immediately prior to our visit to Konza Prairie (KONZ), that site that experienced a significant
400 rain event that led to wet soils that gradually dried out over the course of our time there.
401 This pulse of precipitation increased the soil CO₂ concentration at the top layer above the

402 concentrations in lower layers, leading to negative estimated flux values at the start of the
403 field sampling period. In this case it was only when the soil began to return to a baseline level
404 that the assumptions of the flux-gradient method were again met.

405 Both of the previous cases also provide context for the variable statistical comparisons between
406 field-measured soil fluxes and `neonSoilFlux` outputs (Figure 6). When considering systematic
407 deployment of this method across a measurement network, there are a number of independent
408 challenges that require careful consideration. There are clear tradeoffs between (1) accuracy
409 of modeled fluxes (defined here as closeness to field-measured F_S and the uncertainty reduc-
410 tion factor ϵ), (2) precision (which could be defined by the signal to noise ratio), and (3) the
411 choice of the diffusivity model (Section 4.2.2) or flux computation method (Section 4.2.3). A
412 sensitivity analysis (Figure S2, Supplemental Information) found that flux output uncertainty
413 was dominated by measurement uncertainty (T_S , P , SWC , or CO_2) rather than by the dif-
414 fusivity method used to compute soil flux. Notably, the F_{110} method was least sensitive to
415 measurement uncertainty likely because it best aligns with the surface chamber measurement
416 assumptions.

417 Finally, comparing the effects of different diffusivity estimation methods on the match between
418 modeled and measured fluxes (Figure 5) highlights the sensitivity of F_{ijk} to diffusivity. The
419 comparison between diffusivity estimates compared to field estimated diffusivity (Figure 7)
420 demonstrates that site parameters can dictate which measure of diffusivity is most likely to
421 be accurate in a given environmental context. Site-specific differences are largely a reflec-
422 tion of differences in soil moisture across the sites (Table 1), as not all diffusivity estimation
423 methods incorporate soil moisture equivalently. While we here have compares two approaches
424 to calculate diffusivity (the Millington-Quirk and Marshall models), it may be valuable to
425 evaluate other diffusivity models (e.g. the Moldrup model; Moldrup et al. (1999)) as well. Ul-
426 timately the choice of a particular diffusivity model could be determined based on knowledge

427 of site-specific evaluations or a set of these models could be used to generate a model ensemble
428 average as a means to trade precision for a more general approach.

429 **6.3 Recommendations for future method development**

430 The `neonSoilFlux` package provides several approaches to estimate soil flux using the gradient
431 method. We believe these approaches enable the software to be used across a range of site-
432 specific assumptions (Maier & Schack-Kirchner, 2014). We note, however, that this choice
433 can have a determinative approach on the calculated values. Ensemble averaging approaches
434 (Elshall et al., 2018; Raftery et al., 2005) may be one way to address this problem if the goal is
435 to calculate fluxes using the same method at a diverse range of different sites. Two other ideas
436 would be to apply machine learning algorithms (e.g. random forest) to generate a single flux
437 estimate across diverse sites, or using co-located estimates of net ecosystem carbon exchange
438 from eddy-flux towers to further constrain results or to assess soil flux results for plausibility
439 (Phillips et al., 2017).

440 These challenges notwithstanding, the method used here and made available in the
441 `neonSoilFlux` R package has the potential to produce nearly continuous estimates of flux
442 across all terrestrial NEON sites. These estimates are a significant improvement on available
443 approaches to constrain the portion of ecosystem respiration attributable to the soil. This,
444 in turn, also aids in our ability to understand the soil contribution to the net ecosystem flux
445 measured at these sites using the co-located eddy flux towers.

⁴⁴⁶ **7 Conclusions**

⁴⁴⁷ We used the R package `neonSoilFlux` to estimate soil CO₂ fluxes with the flux-gradient
⁴⁴⁸ method using data from buried soil sensors at NEON terrestrial sites. We compared the
⁴⁴⁹ predicted fluxes to those measured directly using a field-based closed chamber approach. Soil
⁴⁵⁰ fluxes from `neonSoilFlux` were broadly effective at producing estimates of flux comparable
⁴⁵¹ to those measured in the field using a chamber-based technique. However `neonSoilFlux`
⁴⁵² outputs are quite sensitive to a number of issues, including: missing data (and thus gap-
⁴⁵³ filling of input measurement datasets), the selection of soil depths used to best calculate the
⁴⁵⁴ gradient (which may vary between sites), and finally the choice of method used for estimating
⁴⁵⁵ soil diffusivity. The flexibility of the `neonSoilFlux` package allows the user to evaluate each
⁴⁵⁶ of these issues with site-specific knowledge and contexts. Future refinements and subsequent
⁴⁵⁷ validation of `neonSoilFlux` outputs will feed forward into evaluating soil carbon fluxes broader
⁴⁵⁸ spatial scales to enhance understanding of the ways in which soils across diverse ecosystems
⁴⁵⁹ are responding to a changing climate.

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