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Andrew M. Cunliffe and Fabio Boschetti contributed equally to this work.

Key Points:

- Lower-cost, low-frequency eddy covariance (EC) systems yield evapotranspiration and CO₂ fluxes that correspond strongly with high-frequency EC systems
- Lower-cost EC systems enable increased spatial sampling and replication, improving confidence in retrieved evapotranspiration and CO₂ fluxes
- Lower-cost EC systems may therefore address the undersampling and spatial biases in existing EC studies and networks

Supporting Information:

Supporting Information may be found in the online version of this article.

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Strong Correspondence in Evapotranspiration and Carbon Dioxide Fluxes Between Different Eddy Covariance Systems Enables Quantification of Landscape Heterogeneity in Dryland Fluxes

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Abstract The eddy covariance method is widely used to investigate fluxes of energy, water, and carbon dioxide at landscape scales, providing important information on how ecological systems function. Flux measurements quantify ecosystem responses to environmental perturbations and management strategies, including nature-based climate-change mitigation measures. However, due to the high cost of conventional instrumentation, most eddy covariance studies employ a single system, limiting spatial representation to the flux footprint. Insufficient replication may be limiting our understanding of ecosystem behavior. To address this limitation, we deployed eight lower-cost eddy covariance systems in two clusters around two conventional eddy covariance systems in the Chihuahuan Desert of North America for a period of 2 years. These dryland settings characterized by large temperature variations and relatively low carbon dioxide fluxes represented a challenging setting for eddy covariance. We found very good closure of energy and water balance across all systems (within $\pm 9\%$ of unity). We found very good correspondence between the lower-cost and conventional systems' fluxes of sensible heat (with concordance correlation coefficient (CCC) of ≥ 0.87), latent energy (evapotranspiration; $CCC \ge 0.89$), and useful correspondence in the net ecosystem exchange ((NEE); with $CCC \ge 0.4$) at the daily temporal resolution. Relative to the conventional systems, the low-frequency systems were characterized by a higher level of random error, particularly in the NEE fluxes. Lower-cost systems can enable wider deployment affording better replication and sampling of spatiotemporal variability at the expense of greater measurement noise that might be limiting for certain applications. Replicated eddy covariance observations may be useful when addressing gaps in the existing monitoring of critical and underrepresented ecosystems and for measuring areas larger than a single flux footprint.

Plain Language Summary Vegetation around the world is critical to how our planet functions. Plants regulate how sunlight, rain, and even carbon dioxide are used and recycled. In order to learn about plant responses to rain, sunlight, temperature, and climate change, scientists measure the exchanges of water, energy, and carbon between the atmosphere and the land surface. However, the instruments used for these measurements are expensive, so they are only installed in a small number of locations around the entire planet. This is a problem for two reasons: First, these instruments are more common in more wealthy countries giving a distorted view of the world. Second, often only one instrument is installed, meaning we must assume that the area measured is exactly the same as the entire landscape, when this is often not true. To solve this problem, we built a much cheaper version of the instruments, which costs just one-quarter of the usual price. To test our new instruments, we installed them next to the conventional instruments in two locations. We found strong agreement between our cheaper instruments and the high-cost ones. This is good because cheaper instruments could be used more widely to improve the measurement of important ecosystems.

1. Introduction

The eddy covariance technique (EC) is one of the most important tools for the direct investigation of ecosystems, allowing for continuous measurements of land-atmosphere exchanges of energy, water, and carbon dioxide over extents of ca. 1–10 ha (Baldocchi, 2008). The ability to quantify these fluxes via EC makes this technique key



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for advancing understanding of the biotic and abiotic functions of ecosystems (Migliavacca et al., 2011; Raczka et al., 2013) and has led to the establishment of large regional and global networks deploying EC techniques (Baldocchi, 2014; Novick et al., 2018). These EC networks provide data essential to understand ecosystems' roles in the global carbon cycle (Baldocchi, 2020; Baldocchi et al., 2018), responses to perturbations like climate change and land use change (McCalmont et al., 2021), and the potential for nature-based solutions to mitigate anthropogenic carbon emissions (Hemes et al., 2021).

The high cost of conventional EC instruments can limit the number of observations, potentially curtailing the important role that EC can play in improving our understanding of how ecosystems function and are changing. The high cost of conventional EC hardware also means that there are usually single measurement towers with little or no replication in sampling, making it difficult to assess the representativeness and precision of fluxes at the landscape scale (Hill et al., 2017) or even to detect instrument errors (Scott et al., 2015). Consequently, investigations into the spatial variability of fluxes across ecosystems are rare (Davis et al., 2010; Matthes et al., 2014; Post et al., 2015; Sturtevant & Oechel, 2013). The high cost also contributes to substantial bias in the global distribution of EC observations. Existing EC networks are predominantly located in Western Europe, North America, and more recently East Asia and have particularly poor coverage in low- and middle-income countries and over the southern hemisphere in general (López-Ballesteros et al., 2018; Oliphant, 2012; Smith et al., 2019). Poorly sampled areas include several ecosystems considered globally important, such as semiarid grasslands and shrublands, evergreen broadleaf forest, savannah, and tropical dry forest. Drylands alone cover ca. 40% of the land surface, provide ecosystem services that directly support ca. 30% of the global population, and are thought to dominate the trends and interannual variability in the global net ecosystem exchange (NEE) (Ahlstrom et al., 2015; Poulter et al., 2014; Yao et al., 2020).

Understanding and reducing uncertainties in the retrieved ecosystem fluxes require more EC observations. The limited statistical power of EC networks in general and individual systems, in particular, hinders our ability to detect meaningful ecosystem changes (Hill et al., 2017; Hurlbert, 1984). In particular, understanding the ecosystem-scale fluxes requires adequate statistical sampling and/or spatiotemporal extrapolation. In either case, multiple EC systems are required to robustly quantify spatiotemporal changes in energy and carbon dioxide fluxes (Hill et al., 2017) or to corroborate spatiotemporal extrapolations of fluxes (Xu et al., 2017); yet this can quickly become prohibitively expensive when considering the status quo preference for high specification systems. Increasing the availability and reliability of EC observations will increase sensitivity for detecting trends (Baldocchi et al., 2018), while improving the coverage, bias, and precision of empirical observations of ecosystem fluxes. Improved flux estimates will improve the observational constraints on the land surface models used to predict global ecosystem dynamics under future climatic conditions (Baldocchi, 2020; Baldocchi et al., 2018; Chu et al., 2021; Fawcett et al., 2022) and also provide data to help inform management decisions regarding nature-based solutions for climate change mitigation (Hemes et al., 2021; McCalmont et al., 2021).

Advancements in EC instruments and data processing have improved flux reliability and uncertainty estimation (e.g., Zhu et al., 2022); however, the prevalence of nonreplicated installations limit the capacity to detect both instrument errors or biases (Hill et al., 2017; Scott et al., 2015) and landscape-scale errors or biases, for example, at scales greater than the flux footprint (Chu et al., 2021; Hill et al., 2017). Addressing the current lack of replication within EC global networks and underrepresentation of key ecosystems requires either greater investment or lower-cost instrumentation (Baldocchi, 2020). In recent years, lower-cost instrumentation has been developed utilizing more economical anemometers and slow-response hygrometers and CO₂ sensors, which together cost ca. 25% of the conventional systems. However, these systems, which have greater measurement noise (Hill et al., 2017), have not yet been extensively tested in many ecosystems.

This paper provides the first field comparison of lower-cost EC towers in challenging dryland ecosystems. We selected two dryland sites that have been collecting EC data since 2007 as part of the AmeriFlux Network, US-Seg (semi-arid grassland) and US-Ses (semiarid shrubland), and deployed a cluster of four additional lower-cost EC towers at each site with partially overlapping footprints. Our aims were to quantify the spatial variability of energy and CO_2 fluxes and test the performance of the lower-cost, lower-frequency replicated systems relative to the existing conventional EC systems. We had three specific objectives:

1. Compare magnitude of fluxes from conventional EC systems against a colocated lower-cost systems across multiple temporal resolutions.



- 2. Compare the cumulative differences between fluxes from multiple EC systems at each site.
- 3. Assess energy balance and water balance closure from both the lower-cost and conventional systems.

2. Methods

2.1. Study Sites

This study was conducted at two AmeriFlux core sites in the northern Chihuahuan Desert on the McKenzie Flats of the Sevilleta National Wildlife Refuge (SNWR) in central New Mexico, USA. This region is semiarid with a mean annual precipitation of 230 mm (1987-2020), of which ca. 50%-60% usually falls during the North American Monsoon between July and September (Moore, 2021; Petrie et al., 2014). The US-Ses site (34.362°N, -106.702°E) was a C3 shrubland dominated by creosote bush (Larrea tridentata) and some black grama (Bouteloua eriopoda) grass, whereas US-Seg (34.335°N, -106.744°E) was a C4 grassland dominated by black grama (B. eriopoda) with some broomweed (Gutierrezia sarothrae). The elevation of both sites was ca. 1,615 m above mean sea level and the sites themselves were topographically nearly flat. Soils at the grassland site were classified as Turney loamy sand, and soils at the shrubland site were a mix between Turney loam and Nickel-Caliza very gravelly sandy loam (NRCS, 2022). These soils overlay well-developed petrocalcic horizons located at a depth of ca. 0.15–0.45 m (Puttock et al., 2014), and ca. 90% of the near-surface soil carbon was inorganic (Cunliffe et al., 2016). The prevalent wind direction was S, SSE for US-Seg and S, SSW for US-Ses (Figure 1). For earlier analysis on the carbon dynamics of these sites, see Anderson-Teixeira et al. (2011), Petrie et al. (2015), and Biederman et al. (2017). US-Seg and US-Ses were considered good test sites because of their topographic flatness, canopy homogeneity, and near-stationarity of fluxes, facilitating robust comparison between conventional and lower-frequency systems. Further information on both US-Seg and US-Ses is available at https://ameriflux. lbl.gov/sites/site-search/.

Our 24-month study ran from 1 November 2018 to 31 October 2020, commencing at the end of the growing season and hydrological year (Figure S1 in Supporting Information S1; see Petrie et al., 2015 for further discussion of phenology in these ecosystems). During the study, 393 and 374 mm of precipitation were recorded at the grassland and shrubland sites, respectively, ca. 20% below the long-term average (Figure S2 in Supporting Information S1). The seasonal distribution of precipitation was unusual with an uncharacteristically wet spring in 2019 followed by a drier than average summer and then an exceptionally wet November in late 2019 (see Figure S1 in Supporting Information S1 in Supporting Information).

Potential evapotranspiration (PET) was estimated using the Penman-Monteith equation (Beguería & Vicente-Serrano, 2017) and was ca. 560 mm pa for the grassland and 580 mm pa for the shrubland. The long-term aridity indices, defined as the ratio of mean annual precipitation (MAP) to PET, were 0.46 and 0.43 for US-Seg and US-Ses, respectively. Mean annual temperatures during the study were 13.7°C at the grassland and 14.4°C at the shrubland sites.

2.2. Conventional EC Systems

Conventional EC towers have been deployed at US-Seg and US-Ses since 2007 as part of the New Mexico Elevation Gradient and were identical in design and instrumentation (Anderson-Teixeira et al., 2011). Both use a Campbell Scientific CSAT-3 sonic anemometer with a LiCor Li-7500 open-path gas analyzer to measure CO_2 and H_2O fluxes. The sonic anemometer and gas analyzer were positioned 3.2 m above ground with a sensor separation of less than 15 cm. Continuous ancillary observations include air temperature and relative humidity (Vaisala HMP45), rainfall (tipping bucket rain gauges; Texas Electronics, TE525 series), and net radiation (Kipp & Zonen CNR1, installed 3 m above ground on an independent mast 5 m from each main tower). The limited gaps in the rainfall record at each site were filled with observations from nearby meteorological stations (Anderson-Teixeira et al., 2011). Soil temperature (Campbell Scientific T107) and soil moisture content (Campbell Scientific CS-616) were recorded in four pits (two under vegetation and two in inter-vegetation gaps), each with five probes buried at a depth of 2.5, 12.5, 22.5, 37.5, and 52.5 cm. Total soil heat flux was calculated from soil heat flux plates (Hukseflux HFP01) with heat storage from averaging soil thermocouple probes (Campbell Scientific, TCAV).



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Figure 1. (b and e) UAV-derived orthomosaics showing the location of all eddy covariance systems at the grassland (UE-Seg) and shrubland (US-Ses) sites. (a and d) The coordinates are in UTM 13N (based on the NAD83) with an aerial photograph of each site. (c and f) The wind roses were obtained from AmeriFlux (https://ameriflux.lbl.gov/sites/site-search/) and show average climatologies. We sited the systems in order to minimize possible interference with the long-term systems based on the prevailing wind directions.



Half-hourly averages of the covariances were computed from 10 Hz time series after despiking and 3D coordinate rotation. Fluxes were corrected for density fluctuations due to temperature and water vapor using the WPL correction (Webb et al., 1980) and frequency response using the method of Massman (2001). The open-path Li-7500 IRGAs at both sites were calibrated every 6 months. Because instruments were periodically rotated among sites within the New Mexico Elevation Gradient, we also cross-calibrated all Li-7500's across the network to ensure consistent measurements both within and between sites (following the approach described in Scott et al., 2015, more details in Supporting Information S1). The conventional systems are named here as SEG0 (US-Seg) and SES0 (US-Ses).

2.3. Lower-Cost EC Systems

We deployed a cluster of four lower-cost EC systems around each of the two existing EC towers (Figure 1). In each cluster, the first replicated tower ("1") was colocated ca. 7 m away from the conventional towers. We refer to the other three lower-cost systems as "2" (North), "3" (South-East), and "4" (South-West). Systems 2–4 were placed ca. 85 m away from the existing tower, equidistant around a circle (Figure 1). This distribution had logistical benefits as all instruments could be powered from a central 24 V power bank and the close deployment meant that rainfall and radiometer observations of the existing conventional systems could be used for meteorological reference and energy balance calculations.

Our lower-cost EC systems (Figure S3 in Supporting Information S1) consist of a 3-axis Gill WindMaster sonic anemometer for measuring wind vectors and air temperature. The anemometer was mounted on the top of a pole to minimize wind shadowing effects with a measurement height of ca. 6 m above ground. We measured CO_2 concentration with a Vaisala GMP343 and relative humidity with a Honeywell HIH-4000 sensor. The air sample intake was positioned 20 cm below the anemometer sampling point. Air was drawn at 2.5 L min⁻¹ through 6 m of 4.32 mm internal diameter tubing (Synflex) with an ethylene copolymer lining to minimize interactions with water and atmospheric contaminants. The CO_2 and H_2O sensors were configured as closed path sensors in a sensor housing. Table S1 in Supporting Information S1 gives the latitude and longitude of all 10 EC systems. All observations were logged at 10 Hz on the lower-cost systems (although the actual response was slower for some components in this system configuration). The 6 m sampling height of the lower-cost systems was chosen to sample the larger eddies that partially offset the lower-frequency response of the lower-cost gas sensors.

Data from the lower-cost systems were processed using EdiRe software v1.5.0.106 (Clement, 1999). Standard approaches for processing the data were taken following Hill et al. (2017), including spike detection, coordinate rotation, lag removal, frequency response correction, and density corrections. Lags were estimated by calculating the peak in the absolute value of the cross correlation between vertical wind velocity and the relevant scalar. To mitigate the uncertainty inherent in individual half-hourly cross correlations, we modeled the lag as two additive components. The first lag component was a system-specific lag for "dry air conditions" associated with system-specific factors, such as pump performance and filter restrictions (Figure S4 in Supporting Information S1). This component was estimated using a 10-day moving average window for dry conditions with RH < 50% (Figure S5 in Supporting Information S1). The second lag component was an additional relative humidity-dependent H_2O lag that was common for all systems associated with the increasing H_2O lag for closed path systems during humid conditions. Double rotations were applied to each system. We fitted separate Horst and Massman cospectral models (Lee et al., 2004) for each site following the approach set out in Hill et al. (2017). We followed previous frequency correction approaches with corrections for path length, sensor separation, intake tube length, diameter and flow rate, and time responses (Hill et al., 2017). Standard density corrections were applied (Webb et al., 1980); however, for sensible heat, we also calculate density corrections (Schotanus et al., 1983). Example cospectra illustrating the effectiveness of the transfer coefficients used for the lower-cost systems are included in Figures S6 and S7 in Supporting Information S1. The SEG2 system experienced a component failure on 29 March 2020 so LE and NEE observations after this time were excluded from the analysis.

2.4. Quality Control and Gap Filling

A 10-fold recursive 3.5 standard deviation filter was used to remove outliers. For each system, between 16 and 55 half hours were removed for CO_2 , between 91 and 202 half hours for LE, and between 0 and 14 half hours



for sensible heat. This filter removed less than 0.2% of the CO₂ observations, less than 0.6% of the LE observations, and less than 0.04% of H observations. Consistent 0.1 U* filtering was applied to all systems (including SEG0 and SES0). For each site, we calculated the mean friction velocity U* of all 5 EC systems and excluded half-hourly observations where the mean U* was ≤ 0.1 . Across the 10 systems and three fluxes (H, LE, and NEE), gaps averaged 6% of each time series (ranging from 4% to 12%). We then filled gaps in the time series using a robust random forest regression (RFR) model, using the following meteorological parameters as predictors: solar radiation, air temperature, vapor pressure deficit, and other meteorological variables (Zhu et al., 2022). Our RFR model included a time feature extractor to calculate the seasonality and label solar radiation strength as strong (>100 W m⁻²), medium (10–100 W m⁻²), and weak (<10 W m⁻²). We validated our gap-filling approach against an artificial gap scenario with 25% of the total half-hourly observations randomly removed (50% as 30-day gaps, 30% as 7-day gaps, and 20% as 1-day gaps). The RFR model performed substantially better than the widely used Marginal Distribution Sampling (using air temperature, shortwave radiation in and vapor pressure deficit as predictors) (Pastorello et al., 2022). Carbon fluxes are reported relative to the atmosphere with a negative NEE representing a terrestrial sink of carbon.

2.5. Energy Balance Closure

We assessed the energy balance closure for the existing towers and their respective colocated replicated systems by comparing the sum of sensible and latent heat fluxes (H + LE) against net solar radiation (Rn) and the soil heat flux (SHF). The SHF included storage terms. We calculated the Energy Balance Ratio as the ratio of the total cumulative sum of outgoing to incoming radiation over the 2-year period. As the colocated systems (SEG1 and SES1) were not equipped to collect ancillary data, we used Rn and SHF observed at the nearby SEG0 and SES0.

2.6. Footprint Analysis

Each individual tower sampled different spatial footprints, which potentially caused differences in measured fluxes. To assess the contribution of land cover differences in our intercomparison, we calculated the contributing footprint of each tower for each 30-min period using a two-dimensional flux footprint prediction model (http://footprint.kljun.net/) of Kljun et al. (2015). Because the uncertainty of footprint models increases with upwind distance from the receptor (Kljun et al., 2015), we truncated the footprint climatologies at the 80% contour of source weights for our analyses (Chu et al., 2021). We classified land cover into three classes (bare ground, herbaceous, and shrubs) using a supervised maximum likelihood classification of a 2 cm spatial resolution RGB orthomosaic in ArcGIS Pro (v2.1.1, ESRI, Redlands, CA, USA) (see Table S3 and S4 in Supporting Information S1 for accuracy assessment). After classification, the land cover map was resampled to a grid resolution of 1 m using the ArcGIS "Block Statistics" tool, specifying "Unit Type" equal to "map." We estimated the proportion of land cover type sampled within the 80% footprint for each 30-min period and calculated the mean proportion over time for each of the 10 EC systems.

2.7. Statistical Analysis

All analyses and figures were produced using R (v.3.5.1, R Core Team, 2022) and ArcGIS Pro (v2.1.1). All linear models in the plots were fitted using total least squares regression to account for uncertainties on both axes. To evaluate the pairwise correspondence fir different variables and temporal resolutions, we used Lin's concordance coefficient (CCC) (L. I. Lin, 1989, L. I.-K. Lin, 2000) using the DescTools package (Signorell et al., 2021).

3. Results

3.1. Conventional Versus Lower-Cost EC Systems

We found strong correspondence in the daily sensible heat flux (H) between the conventional and colocated lower-cost systems with concordance correlation coefficient (CCC) of 0.87 and 0.94 for SEG and SES, respectively, and systematic biases ranging from <0.01% to ca. 13% (Figures 2a and 2b). We also found strong correspondence in daily latent energy flux (LE) between the conventional and colocated low-frequency systems with CCC > 0.89 and a bias of 7% in the Seg (Figure 2c) and ca. 22% in the Ses site (Figure 2d). This strong





Figure 2. Comparison of sensible heat (H), latent energy (LE), and CO_2 (net ecosystem exchange) daily fluxes between colocated conventional and low-frequency systems at both sites. The gray-dashed lines indicate the 1:1 relationship, black lines indicate linear models fitted with total least squares regression to account for uncertainties on both axes, and CCC is correlation concordance coefficient.



correspondence for H and LE also exists on the half-hourly scale, especially for H with CCC ≥ 0.9 (Figures S8a and S8b in Supporting Information S1), but also for LE with CCC ≥ 0.66 . Correspondence was stronger on the monthly timescale, increasing to CCC = 0.97 for H in both sites and for LE in SEG, and stays relatively the same for LE in SES (0.89 and 0.87 for daily and monthly CCC, respectively) (Figures S9a and S9b in Supporting Information S1). The fitted slope for H was very close to unity for both sites on the daily and monthly scale with the low-frequency generally capturing the same or a slightly higher sensible heat flux (12.7%, 9.8%, and 3.6% higher for daily-scale SES, monthly-scale Ses and monthly-scale SEG, respectively). On the contrary, the lower-cost system captured a lower latent heat flux compared to the conventional system at both sites on both daily and monthly scales. This was especially pronounced in SES with differences of up to 22% (Figure 2d). It is important to note that all fitted lines have an intercept that is approximately zero at all scales, indicating that there is no bias in fluxes when they approach zero. This is especially important for carbon dioxide fluxes, which are discussed next.

The lower-frequency EC yielded noisier carbon flux estimates (NEE), resulting in CCC of just 0.13 on the half-hourly scale (Figures S8e and S8f in Supporting Information S1) and 0.4–0.46 on the daily scale (Figures 2e and 2f) between the conventional and colocated low frequency systems. When integrated on a monthly scale, the correspondence for NEE between the two systems increases considerably with CCC of 0.71–0.72. The intercept of the fitted line at zero at all scales increases the confidence in the ability of both systems to capture the transition from carbon source to sink correctly both during the day and between seasons. However, we still see large differences in the magnitude of these sinks and sources with the lower-cost systems generally capturing lower values (slopes of ~0.48 and ~0.53 for the daily and monthly scales in Figures 2e and 2f, S9e, and S9f in Supporting Information S1, respectively).

3.2. Site-Level Flux Comparisons

H values measured from the low-frequency EC systems were in very good agreement, being derived from the same model of sonic anemometer (Table S5 in Supporting Information S1). We found strong correspondence in latent energy (evapotranspiration) fluxes at the site-level, particularly within the lower-cost systems although the conventional systems estimated ca. 5%–10% more evapotranspiration (Figures 3a and 3b). The cumulative water flux from latent energy closely tracked the cumulative precipitation, indicating that evapotranspiration was limited by water availability in this setting (Figures 3a and 3b). Cumulative evapotranspiration ranged from 341 to 410 mm m⁻² after 24 months (Table S5 in Supporting Information S1), closely tracking precipitation (Figure 3).

Cumulative NEE ranged from 3.6 to -45.1 g C m⁻² for NEE after 24 months (Figures 3c and 3d; Table S5 in Supporting Information S1), equating to annual fluxes of 0.02 to -0.23 Mg C ha⁻¹ y⁻¹ over the 24-month period. The four lower-cost towers at each site exhibited larger variation between them compared to their tight agreement for the water flux. Still, all systems largely agreed with regard to the timing of changes in the flux but often exhibited different response magnitudes. The conventional EC systems indicated larger increases in carbon dioxide uptake during the growing season, when NEE dropped almost twice as much for both SEG0 and SES0 compared to all the lower-cost systems, corresponding to the relationship observed between the daily fluxes at the two systems (Figures 2e and 2f).

Our footprint analysis indicated that the probability of sampling bare ground, herbaceous, and shrub land covers after averaging over time was very consistent among all 5 EC systems at each site (Figure 4). This was because the spatial patterns of land cover were relatively consistent across the 80% sampled footprint area despite the fine-scale heterogeneity of land cover in these ecosystems. This analysis confirmed partial overlaps between the sampled footprints of different towers that result in some pseudo-replication. The similar proportion of land cover is sampled by each system suggesting that differences in retrieved fluxes were unlikely to arise from differences in sampled land covers. Due to differences in the instrument height, the footprints for the lower-cost EC towers were ca. eight times larger than the existing towers, but the smaller footprints sampled by the longer-term conventional EC towers (SEG0 and SES0) appear to be representative of the wider area sampled by the taller towers of the lower-cost systems (Table 1, Figure 4).





Figure 3. (a and b) Cumulative water flux through precipitation and evapotranspiration derived from latent heat flux and (c and d) Net Ecosystem Exchange at the grassland and shrubland site for all of the systems. Note that the record from SEG2 is incomplete due to a component failure.

3.3. Energy Balance Closure

We found the energy balance closure was similarly very good (within $\pm 9\%$ of unity) for the low-frequency and conventional EC systems, regardless of the linear model slope (Figure 5) or energy balance ratio method (Table 2). Increasing confidence that the inferred fluxes capture most of the energy fluxes in these sites. The cumulative energy balances for the SEG0, SEG1, SES0, and SES1 systems exhibited a relatively small unaccounted for loss in the measured fluxes (Figure S10 in Supporting Information S1), which amounted to less than 6.6% of the net incoming energy over the 2 years. The similarity of the closure between the conventional and the lower-cost systems can be explained by the good agreement in both LE and H when comparing these two systems.

4. Discussion

In this study, we deployed multiple lower-cost EC towers across two dryland sites to quantify spatial variability at the intra-site level and test replicability of EC observations. We believe that this was the first time such replication has been possible in drylands using fully independent instruments for an extended period (24 months). These dryland grass and shrub ecosystems characterized by extremely low fluxes present one of the hardest test cases for EC. Our custom-made lower-cost EC systems produced estimates of energy, evapotranspiration, and carbon fluxes that were broadly consistent with each other and adjacent conventional eddy covariance systems.







4.1. Water and Energy Balance and NEE

All EC systems demonstrated good closure of both the water balance closure (Figures 3a and 3b) and the energy balance (Table 2, Figures 5, S8, and S9 in Supporting Information S1). The lower-cost systems had a higher random uncertainty ("noise"), particularly at the half-hourly time step (Figure S8 in Supporting Information S1). This noise hinders the analysis of very short term correspondence between systems or immediate responses over short time periods, for example, of NEE to atmospheric phenomena, such as cloud cover or precipitation or soil moisture; however, it would still be possible to combine observations over a season to study light response curves, for example,

We found useful correspondence in NEE at the daily and monthly temporal resolutions, especially with regard to the timing of changes in fluxes. Our results suggest that the lower-cost systems estimate smaller sink values during the growing season compared to the sink estimated by the conventional systems. While measurements of changes in biomass and soil carbon would be needed to corroborate the EC estimates, the impact of potential errors should be considered when interpreting the cumulative sinks relative to the magnitude of the net carbon sink. We expect this consideration to be especially relevant in sites with near-zero net carbon fluxes. As for differ-

ences between the individual lower-cost systems, we did not expect to see large differences in cumulative NEE, but rather for them to be similar such as was observed for H and LE. We were not able to explain these differences using the extent of areal coverage of land cover classes within time-averaged tower flux footprints. More work is needed to determine to what extent differences in cumulative NEE may arise from the inherent ecosystem variability in factors, such as the distribution of plant size, heterogeneity in local soil texture that could also affect local soil moisture, or challenges measuring relatively low net fluxes.

4.2. Reducing Barriers to Deployment of EC Systems

The lower cost of our EC systems in terms of both hardware and maintenance (a visit every 4 months to replace intake filters) allowed us to replicate measured fluxes and assess the representativeness of the existing EC systems with a total budget comparable to a single conventional tower. By using less expensive components, the overall hardware expense of the lower-cost EC system is ca. ¹/₄ that of the conventional system. For example, the Gill Wind-Master sonic anemometer, Vaisala GMP343 CO₂ sensor, and Honeywell HIH-4000 relative humidity sensor cost ca. 30%, 10%, and 1%, respectively, relative to the current state-of-the-art sensors popular in North America and Europe (such as the Campbell Scientific CSAT-3 anemometer, open-path Li-COR 7500, or closed-path Li-COR 7200).

Our lower-cost (closed-path) systems, EC systems, required <12 W, which were similar to the conventional (open-path) systems. This efficiency is valuable for both for the hardware costs and logistical feasibility of powering spatially distributed EC systems to replicate sampling across ecosystems, especially in remote locations. Although the lower-cost systems were not instrumented to collect ancillary data in this study, we estimated that the addition of one net-radiometer, 20 soil water content sensors, one soil temperature and RH probe,

and two multiplexers to one of our systems would add <0.3 W to the total power requirement. These low-power requirements for ancillary data support stand-alone installations.

Inexpensive EC systems offer the ability to deploy multiple systems to achieve replication, or even to deploy EC systems where they would otherwise not be possible (Hill et al., 2017). Such deployment could address the existing gaps in the current global observation networks by better sampling spatiotemporal variation in ecosystems. An application in this last case would be using multiple systems to monitor across transitional ecotones. Lower-cost EC systems also greatly enhance the opportunity for sampling biomes that have traditionally received lower attention either because of the relatively low magnitude of their gas exchanges or remoteness. While we acknowledge that

Table 1

Average Area of 80% Footprint Sampled by Each Eddy Covariance Technique System (Units in ha)

		Grassland	Shrubland
Conventional system	"0"	0.9	0.5
Lower-cost system	"1"	7.0	4.2
	"2"	7.0	4.2
	"3"	7.0	4.2
	"4"	6.9	4.2





Figure 5. The half-hourly energy balance closure was similar across the conventional and lower-cost systems. Full energy balance closure for SEG0 and SES0 (a and b) and the corresponding colocated towers SEG1 and SES1 (c and d) calculated by plotting the sum of sensible and latent heat fluxes (H + LE) against net solar radiation (Rn) and the sum of soil heat flux and storage (G).

this imbalance has been improving—see Figure 1 in Smith et al. (2019)—the coverage biases have not yet been adequately resolved. Additional observations can facilitate the detection of instrument errors or biases (Boschetti et al., 2019; Scott et al., 2015) and enable better quantification of measurement uncertainty, which is essential for the observational constraint of increasingly complex land surface models (Chu et al., 2021; Piao et al., 2020).

5. Conclusion

We deployed lower-cost EC systems in clusters around two existing EC towers in the Northern Chihuahuan Desert over a 24-month period. The retrieved fluxes of heat and latent energy were very similar between the colo-

Table 2

Energy Balance Ratio, Defined as the Ratio of Outgoing to Incoming Radiation

	Grassland	Shrubland
Conventional system	0.926	0.946
Lower-cost system	0.965	0.985

cated conventional and lower-cost systems. We found useful correspondence in NEE despite this very low NEE environment representing a difficult test case for EC. Energy balance closure was similarly good across the conventional and lower-frequency systems with excellent energy balance ratios.

Within each site, cumulative fluxes of H, LE, and NEE were broadly consistent across the 5 EC systems (one conventional and four lower cost). The footprint analysis indicated that proportional land cover when averaged over



time was similar between sampled footprints and among systems, suggesting that any differences in retrieved fluxes were unlikely to arise from differences in the sampled land cover. While the lower-cost systems were less precise than the conventional systems, particularly for NEE, either averaging half-hourly fluxes to the daily time step or averaging the fluxes derived from three or more lower-cost systems yielded levels of precision comparable to the conventional systems.

Our demonstration of these EC systems with hardware costs of just one quarter of the conventional systems opens new possibilities for the way that EC can be deployed around the world. At existing EC installations, a colocated lower-cost system could be deployed to help validate observations and minimize gaps. Replicated arrays of systems could be used to test spatial variations in fluxes across sampling units/ecosystems. Stand-alone installations could be deployed by groups that are currently precluded from entering the EC community by the high hardware costs, helping to address substantial existing sampling biases. Together, these opportunities afforded by lower-cost, low-frequency EC systems represent scope for expanding flux sampling around the world.

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

Data Availability Statement

Post-processed half-hourly data from AmeriFlux systems are available at https://ameriflux.lbl.gov/login/?redirect_to=/data/download-data/ and the data from the low-frequency systems are archived with the NERC Environmental Information Data Centre (https://doi.org/10.5285/e96466c3-5b67-41b0-9252-8f8f393807d7). The code repository is archived on Zenodo (https://doi.org/10.5281/zenodo.4730586).

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