Stable isotopes contain substantial additive information about terrestrial carbon and water cycling.

Bonan Lia,b,c,d Stephen P. Gooda,b, Richard P. Fiorellae,f,g, Catherine E. Finkenbinera,b, Gabriel J. Bowene,f, David C. Nooneh, Christopher J. Stilli, William R.L. Andereggf,j,h

aDepartment of Biological & Ecological Engineering, Oregon State University

bWater Resources Graduate Program, Oregon State University

cCollege of Earth Ocean and Atmospheric Sciences, Oregon State University

dDepartment of Biological & Agricultural Engineering, University of Arkansas

eDepartment of Geology and Geophysics, University of Utah

fGlobal Change and Sustainability Center, University of Utah

gEarth and Environmental Sciences Division, Los Alamos National Laboratory

hDepartment of Physics, University of Auckland

iDepartment of Forest Ecosystems and Society, Oregon State University

jSchool of Biological Sciences, University of Utah

hWilkes Center for Climate Science and Policy, University of Utah

Corresponding author: Bonan Li

Email:libon@oregonstate.edu

**Abstract**

Stable isotope ratios of H (*δ2H*), O (*δ18O*), and C (*δ13C*) are linked to key biogeochemical processes of the water and carbon cycles; however, the degree to which isotope-associated processes are reflected in macroscale ecosystem flux observations remains unquantified. Here through formal information assessment, new measurements of *δ13C* ofnet ecosystem exchange (*NEE*) as well as *δ2H* and *δ18O* of latent heat (*LH*) fluxes across the United States National Ecological Observation Network (NEON) are used to determine conditions under which isotope measurements are informative of environmental exchanges. We find all three isotopic datasets individually contain comparable amounts of information about *NEE* and *LH* fluxes as wind speed observations. Such information from isotope measurements, however, is largely unique. Generally, *δ13C* provides more information about *LH* as aridity increases or mean annual precipitation decreases. *δ2H* provides more information about *LH* as temperatures or mean annual precipitation decreases, and also provides more information about *NEE* as temperatures decrease. Overall, we show that the stable isotope datasets collected by NEON contribute non-trivial amounts of new information about bulk environmental fluxes useful for interpreting biogeochemical and ecohydrological processes at landscape scales. However, the utility of this new information varies with environmental conditions at continental scales. This study provides an approach for quantifying the value adding non-traditional sensing approaches to environmental monitoring sites and the patterns identified here are expected to aid in modeling and data interpretation efforts focused on constraining carbon and water cycles’ mechanisms.

**Keywords:** isotope, carbon flux, water flux, NEON, information theory

**1. Introduction**

Understanding the interactions and drivers of water and carbon exchanges between terrestrial ecosystems and the atmosphere is crucial to illuminate processes driving Earth’s current climate as well as forecasting impacts of future change on ecosystems and the climate itself (Jung *et al* 2011, Piao *et al* 2020). To date, significant efforts have been made to monitor terrestrial carbon and water fluxes, including the widespread development of macroscale eddy covariance (EC) networks to measure ecosystem fluxes (Baldocchi 2014, Schimel and Schneider 2019). EC flux towers can measure continuous net ecosystem exchange (*NEE*) of CO2 between the land surface and atmosphere at various frequency. Similarly, EC measurements of latent heat flux (*LH*), representing evaporation and transpiration from soils, water bodies, and plant canopies, provides valuable information for understanding regional and global water budgets as well as agricultural applications (Zhou *et al* 2018, Zeng *et al* 2020). Flux measurements have been used for a variety of environmental applications such as calibrating and validating remotely sensed flux estimations (Jia *et al* 2012), parameterizing land surface models (Williams *et al* 2009), modeling seasonal crop coefficients (Li *et al* 2008), and investigating disturbance impacts such as post-fire carbon balance (Lupascu *et al* 2020). While measurements of *LH* and *NEE* can quantify fluxes themselves, new kinds of data are needed to refine knowledge of the processes driving these fluxes which are central to the carbon and water cycles.

To improve understanding of Earth system processes, the geoscience community has developed a wide array of advanced measurements to complement landscape scale flux data to help quantify environmental processes. These include studies focused on stable isotope fluxes (Dubbert and Werner 2019), Carbonyl Sulfide (COS) (Whelan *et al* 2018), various radiometric indices such as thermal (Still *et al* 2021) and solar induced fluorescence (SIF) (Guan *et al* 2016), and even environmental DNA (URycki *et al* 2022). Prominent among these techniques, naturally occurring water and carbon isotope measurements have been shown to be a powerful tool for understanding a wide array of ecohydrological and biophysical processes because distinct processes are, and are not, often associated with known isotope transformations (i.e., fractionation effects) (Bowen and Good 2015). Water isotope ratios (*δ2H* and *δ18O* in water) have been used to partition evapotranspiration into evaporation and transpiration, as evaporated and transpired fluxes from the same ecosystem may have distinct isotope ratios (Xiao *et al* 2018, Berkelhammer *et al* 2013). *δ13C* values of CO2 have also been applied to separate *NEE* into its constituent fluxes, as the isotopic composition of photosynthesis can differ from that of ecosystem respiration (Lee *et al* 2020). Previous network-based studies of *δ2H*, *δ18O* and *δ13C* examined patterns across distinct ecosystems using cryogenic baths and flask samples; however, the poor temporal sampling and spatial coverage has limited these approaches to understand ecosystem-scale processes (Orlowski *et al* 2018, Gemery *et al* 1996). The development of automated laser spectroscopy systems mounted on EC towers provides new opportunities to obtain long term spatially and temporally resolved atmosphere profiles of these isotopes (Fiorella *et al* 2021). The recently launched National Ecological Observatory Network (NEON) provides the first standardized measurements of the stable isotope ratios of H2O vapor and CO2 for ecosystems across the USA that can be used to estimate *δ2H* and *δ18O* of *LH* and *δ13C* of *NEE* (Finkenbiner *et al* 2022).

The development of advanced ecosystem measurements across networks such as NEON presents new scientific possibilities; yet this also raises the fundamental question of how useful new, and often expensive, data streams are for constraining uncertainties in targeted environmental processes. Many advanced measurements are made at considerable cost and effort, yet their full value as a source of information beyond traditional meteorological observations (e.g., vapor pressure deficit, *VPD*, air temperature, *T*, global radiation, *Rg*, and windspeed, *u*), is rarely demonstrated in a formal sense, especially within continental-scale networks where variability in environmental conditions occurs across a much wider range than individual sites. Here we capitalize on recent advances in information theory to assess the information content of NEON stable isotope data. These advances allow for the formal quantification of linear and nonlinear interactions between variables (termed mutual information) (Cover and Thomas 2005), as well as approaches to diagnose how unique the information provided by new data sources is relative to others (Goodwell and Kumar 2017, Williams and Beer 2010). This study addresses three related questions: (1) Do new observations (here *δ2H,* *δ18O,* and *δ13C* values) contain useful information about the bulk *NEE* and *LH* fluxes across North America? (2) Can any of the information provided by new (isotope) measurements be obtained from other meteorological variables? And (3) under which environmental conditions do these new measurements provide the most additional information? In doing so, this study provides a generalizable approach for evaluating the conditions under which novel geoscience data is helpful for understanding the Earth system. It also formally quantifies the conditions under which environmental processes associated with transformations of stable isotope ratios, as measured systematically within continental scale networks*,* are a greater contribution to overall environmental exchanges. This approach thereby provides key process level benchmarks for advancing research into Earth’s integrated carbon and water cycles.

**2 Materials and methods**

**2.1 Study sites and data preparations**

This study was conducted at terrestrial sites that are part of the United States National Ecological Observatory Network (NEON), which is a continental scale research platform for understanding the ecological responses to climate change, land use change, and species invasion (Barnett *et al* 2019). We used the 30-minute aggregated *NEE*, *LH*, global radiation (*Rg*), air temperature (*T*), and the two-dimensional wind speed (*u*) datasets from the NEON’s eddy covariance bundled datasets (NEON 2022a). The vapor pressure deficit (*VPD*) data were derived based on NEON’s relative humidity, temperature, and barometric pressure products (NEON 2022b). The *NEE* and *LH* data were filtered for periods of low turbulence based on friction velocities (*u\**) then gap-filled using the marginal distribution sampling method (Wutzler *et al* 2018). The gap-filled and *u*\* filtered 30-minute fluxes were further averaged on a daily scale to facilitate future analysis. All 30-minute meteorological variables except wind speed were gap-filled using the marginal distribution sampling mentioned above. The gap-filled meteorological variables were then averaged to daily scale. Extreme values in daily flux and meteorological datasets were further processed using an inter-quantile filter (Goodwell and Kumar 2017). More details can be found inSupplemental information. Daily stable isotope ratios (*δ2H,* *δ18O,* and *δ13C*) of *NEE* and *LH* were obtained from a recently published dataset (Finkenbiner *et al* 2022), which was derived based on the isotope composition of carbon dioxide and water vapor from EC tower profiles across NEON sites. The *δ18O* values were converted to deuterium excess (*d*) via *d = δ*2*H* – 8 \* *δ*18*O* (Dansgaard 1964).

**2.2 Information measures**

In this study the mutual information metric, *I*(X;Y), was chosen to analyze how different meteorological variables share information about ecosystem fluxes because it has the advantage over traditional metric (e.g., correlation coefficient) of capturing both linear and non-linear dependencies between two variables. It represents the reduction in uncertainties of one variable given the knowledge of another variable. Formally, mutual information is a measure of how two random variables are probabilistically dependent on each other in the unit of bits (Cover and Thomas 2005). Probabilistically, the mutual information can be expressed as:

|  |  |
| --- | --- |
| *I*(X;Y) = | (1) |

where *p*(*x*), *p*(y), and *p*(x,y) are the probability density functions of random variables X, Y, and {X,Y} respectively.

The multivariate mutual information, *I*(X,Y;Z), of a single random variable (Z) and a set of random variables {X, Y} characterizes the amount of uncertainty inZ that can be reduced by the knowledge of {X, Y} and can be expressed as:

|  |  |
| --- | --- |
| *I*(X,Y;Z) = | (2) |

where *p*(z), *p*(x,y), and *p*(x,y,z) are the probability density functions of variables Z, {X,Y}, and {X,Y,Z}, respectively and were estimated using a kernel density estimation (KDE) method with a gaussian kernel and Silverman bandwidth selection method (Silverman 2018). To evaluate the above information metrics, we rescaled each data point to a common range of [0, 1] before using KDE. We then evaluate the probability density functions from 0 to 1 with a step size of 0.05.

We computed the pairwise mutual information (e.g., *I*(*VPD*;*NEE*), *I*(*VPD*;*LH*), etc.) shared among *VPD*, *T*, *Rg*, *u*, *δ13C*, *δ2H*, and *d* about *NEE* and *LH* iteratively. Due to the limitation of isotope datasets, we computed the mutual information of each variable with the *NEE* and *LH* by subsampling 100 data points without replacement 500 times to ensure equal constituent data counts in mutual information calculations. Then, the mutual information of the variable of interest and the flux is computed as the average mutual information across 500 resamplings. The mutual information contents computed above are evaluated for statistical significance (refer to Supplemental information for details).

**2.3 Partial information decomposition**

The multivariate mutual information can be decomposed into different informational components via a partial information decomposition framework (PID) (Goodwell and Kumar 2017, Goodwell et al 2018, Williams and Beer 2010). This framework captures how the different source variables interactively influence a target variable of interest, which can possibly reveal the process that relates source variables and a target without any modeling assumptions. The PID can decompose *I*(X,Y;Z) into: (1) unique information (U) that is only provided byX or Y solely to Z; (2) synergistic information (S) that is the information provided to the Z when X and Y act jointly; (3) redundant information (R) that is the overlapping information provided both by X and Y to the Z (Goodwell and Kumar 2017). The PID framework can be formulated as

|  |  |
| --- | --- |
| *I*(X,Y; Z) = + + R + S | (3) |
| *I*(X; Z) = + R | (4) |
| *I*(Y; Z) = + R | (5) |

Whereand are the unique information of X and Y to Z, respectively. R and S are the redundant and synergistic information of X and Y to Z, respectively. All PID components are non-negative real numbers in unit of bits (Goodwell and Kumar 2017).

In this study, we quantified the information flow between each flux and each isotope ratio by leveraging the PID framework (Goodwell and Kumar 2017). We defined the decomposed information components that the isotope ratios provided to the bulk fluxes as the averaged unique information across all meteorological variables (*VPD*, *T*, *Rg*, and *u*). As with computing the individual mutual information, we also subsampled 100 data points from each dataset without replacement 500 times. The partial information components of the isotopes were then computed as the averaged information components from 500 iterations. The significance tests were performed similarly to mutual information (refer to Supplemental information for details).

**3. Results**

Informational analysis shows that isotope data (*δ13C, δ2H,* and *d*)and traditional meteorological data (*Rg*, *T*, *VPD*, *u*) each contain significant information about temporal variation in *NEE* and *LH* fluxes (Fig. 1). This formally demonstrates that *NEE* and *LH* become less uncertain given the knowledge of isotope data or meteorological data throughout the NEON sites. We find that *Rg*, *T*, and *VPD* observations consistently contain more information aboutenvironmental fluxesthan the isotope data products. This analysis shows that wind speed (*u*) provides comparable amount information about *NEE* and *LH* fluxes(Fig. 1) as the isotope data. Though the information provided by *Rg*, *T*, and *VPD* is larger than the information from *u* and the isotopes, *u* is nevertheless one of the well-established drivers of surface-atmosphere water and carbon exchange and is commonly measured at meteorological stations worldwide (Yusup and Liu 2020).

In general, individual variables tend to share more information with *LH* than *NEE* (Fig. 1). This indicates that *LH* is generally more easily constrained and predicted based on these environmental observations, possibly because it more strongly captures isotopic differences in the contributing one-way flux compared to *NEE* which is the net sum of two opposing fluxes with less distinct isotope ratios. Instead of *δ13C* values best constraining *NEE* and *δ2H* or *d* values best constraining *LH,* we find that *δ2H* values on average provide slightly more mutual information than *δ13C* values for both *NEE* and *LH* fluxes*;* however, both these (i.e., *δ2H* and *δ13C*) are more informative than *d.* *NEE* is a quantity that encompasses downward carbon uptake via plant photosynthesis and carbon release upward through respiration (Reichstein *et al* 2005) while water, as represented by *LH*, is evaporated upward during evapotranspiration. *δ2H* links with the phase transformation of water that is strongly temperature dependent (Xiao *et al* 2018). Therefore, *δ2H* is more likely to carry slightly more information about *LE* and *NEE* than *δ13C*.The amount of information that can be inferred from isotopes (and other variables) about *NEE* and *LH* is highly unlikely to be obtained by random processes (*p* < 0.01).

We decomposed and evaluated the multivariate mutual information betweenenvironmental fluxes, isotope ratios, and other variables (Fig. 2). These results demonstrate that most of the information provided by the isotopes about *NEE* and *LH* is unique to these measurements (*δ13C* and *δ2H*). This unique information (i.e., the information contribution that is contributed only by one variable to the target variable) provided by *δ13C* and *δ2H* values about *LH* is generally higher than the unique information provided about *NEE.* The unique information provided by *δ13C* and *δ2H* values is higher than that contained within *d* values for both *LH* and *NEE* fluxes. The unique information is found to vary spatially across the NEON sites (Supplemental Fig. S1). All the unique information provided by the isotope ratios is statistically significant and highly unlikely to be obtained at random (*p* < 0.01).

In addition to the unique information that *δ13C*, *δ2H*, and *d* values contain about *NEE* and *LH* fluxes, a smaller amount of synergistic (i.e., the information component when isotope and other variables act jointly to provide information about ecosystem fluxes) and redundant information (i.e., the overlapping information that isotope or other variables contribute to ecosystem fluxes) is also presented (Supplemental Fig. S2 and S3). Among all the isotope measurements, the synergistic component of *d* values is slightly larger for *NEE*. In general, redundant information tends to be smaller than the unique and synergistic components. The unique and redundant information linking isotopes with *NEE* and *LH* are statistically significant (*p* < 0.01).

The total additional information, represented by the sum of the synergistic information and the unique information (*U+S*), provided by each flux isotope composition to *LH* and *NEE* varies spatially across NEON sites (Fig. 3). *δ*13*C* contributes the most substantial information about *NEE* and *LH* in the Northeastern US (i.e., New Hampshire) and southwestern US (i.e., New Mexico), respectively (Fig. 3a and Fig. 3d). In northern Alaska, *δ*2*H* contributes the largest amount of additive information to *NEE* (Fig. 3b). There is an increased possibility of observing more additive information of *δ*2*H* about *LH* at site with higher latitude (Fig. 3e). The highest additional that *d* provides to *NEE* and *LH* were observed in Virginia (Fig. 3c) and Wyoming (Fig. 3f), respectively. The fraction of the total information for isotopes (*U+S+R*) about *NEE* that is additive, i.e. (*U+S*)/(*U+S+R*), is 0.95 for *δ13C*, 0.92 for *δ2H*, and 0.99 for *d*, respectively). For *LH,* *δ2H* and *δ13C* provided more additive information than *d* (Fig. 3d-f). The fraction of additive information about *LH* is 0.89 for *δ13C*, 0.84 for *δ2H*, and 0.94 for *d*, respectively. The additive information of *δ13C*, *δ2H*, and *d* relating to *LH* has larger variability among sites than that relating to *NEE* (Fig. 3). All the additive information of these isotopes relating to *NEE* and *LH* is statistically significant (*p* < 0.01).

**4. Discussion**

Our analysis provides a rigorous evaluation of the quantitative value of isotope ratios to provide useful information about carbon and water fluxes across continental scale gradients. For these bulk fluxes, we showed that the information individually provided by these isotopes was similar to the amount of information provided by wind speed measurements, while providing less information than atmospheric vapor pressure deficit, air temperature, and radiation measurements (Fig. 1). The meteorological observations evaluated here are commonly used to drive forecasts of environmental processes (Cosgrove *et al* 2003, Rodell *et al* 2004) and thus serve as a benchmark for environmental data. A prior *NEE* simulation showed that radiation was consistently the most sensitive predictor for the simulation of *NEE* at maize fields with distinct irrigation practices (Safa *et al* 2019). Similarly, a sensitivity analysis on global evapotranspiration models indicated that net radiation was one of the influential input variables (Talsma *et al* 2018). Our results are consistent with the fundamental notion that solar radiation is the basis for all ecosystem functions (Yetemen *et al* 2015) (excluding rare energy transformations) and drives most diurnal variation in air temperature and vapor pressure deficit and therefore is more likely to share higher amount of mutual information individually with *LH* and *NEE*, with temperature and moisture levels of secondary importance and isotope metrics and wind speed of tertiary importance.

The meteorological variables evaluated here are known to be inter-related to some extent. For instance, the vapor pressure deficit is strongly dependent on air temperature due to the Clausius-Clapeyron relationship (Clausius 1850) and air temperature is tightly related to the amount of radiation as well as to sensible heat fluxes. Past studies have highlighted how *NEE* and *LH* respond to changes in vapor pressure deficit, air temperature and radiation across various scales, seasons, and ecosystems (Chen *et al* 2020, Niu *et al* 2012, Gu *et al* 2006). Vapor pressure deficit was found to have direct effect on surface energy partitioning as high vapor pressure deficitrepresents high atmosphere demand and hence high *LH* with constant surface conductance (Tong *et al* 2022, Wang *et al* 2019). Yet, high vapor pressure deficit can reduce stomatal conductance and thereby reduce plant photosynthesis (Grossiord *et al* 2020). Wind speed can modulate the rate of evapotranspiration and thereby *LH* (Yang *et al* 2019, Liu and Zhang 2013). The different effect of vapor pressure deficit and wind speed on *LH* may be underrepresented by other metrics but can be captured if evaluated using information theory-based metrics like those explored here.

Information carried by these isotope ratios was found to be distinct from the traditional meteorological variables examined here. It is also crucial to understand how different variables interactively provide information to a target of interest because knowledge of the interdependencies between the inputs and outputs of a studied system is fundamental for model uncertainty characterization (Ruddell *et al* 2019, Li and Good 2021, Gong *et al* 2013). In fact, one of the challenges for land surface models is increasing process complexity with the integration of a set of sub-models with the expansion of input dimensions (Fisher and Koven 2020), which can increase the risk of model “equifinality”. Moreover, numerous models have been developed to estimate ecosystem fluxes (Wood 2021, Su 2002, Veroustraete *et al* 1996). However, these methods often require some assumptions or simplifications, which can be subject to significant uncertainty (Papale *et al* 2006, Zhao *et al* 2020). In general, it may be more desirable for each of the inputs in a model to provide unique or synergistic pieces of information (Wibral *et al* 2017), which can potentially capture different processes relating to the target (Goodwell *et al* 2018). Therefore, the construction and simplification of ecosystem models should move towards a direction that maximizes unique information provided by each input.

The decomposition of the multivariate mutual information between isotopes, other meteorological variables, and the bulk fluxes offers an opportunity to elucidate how much of the information from isotopes is transferred to the bulk fluxes (*NEE* and *LH*). In this study, the portion of unique information from isotopes measurements for carbon and water isotopes was statistically significant. This suggests that processes driving variation in isotope ratios may influence these fluxes via distinct pathways. We observed inter-site variations in the unique information provided by the isotopes, indicating that the unique information may be dependent on site-specific conditions such as aridity and precipitation. There is a higher chance that *δ13C* contributes more information about *LH* under drier or lower precipitation conditions (Supplemental Fig. S4). Additionally, both *δ13C* and *δ2H* tend to provide more distinct insights into *NEE* and/or *LH* in cooler or lower precipitation conditions. This suggests that the patterns of bulk fluxes can potentially be better characterized and predicted with the isotopes included as an additional constraint.

The additional information provided by isotopes to these bulk fluxes are described by the sum of unique information and synergistic information. Our analysis demonstrates that fusing isotope data products with more traditional datasets can potentially lead to better monitoring and prediction of *NEE* and *LH* in a process modeling framework, as these isotope datasets provide additional information beyond traditional meteorological variables and are associated with known physical mechanisms. The incorporation of isotope datasets into artificial intelligence (AI) and machine learning (ML) models, especially explainable AI models, can potentially improve predictive accuracies and enhance our understanding of ecosystem fluxes. Nevertheless, uncertainties can be introduced when incorporating isotope dataset to models with larger spatial scale. It is challenging to include isotope datasets to models that require larger spatial scale isotope datasets, as they are often hard to acquire. Researchers might also consider different incorporation strategies in different ecoclimate regions. In addition, the amount of added information of the isotope datasets is likely to vary across sites, climate, and ecosystems. To assess this, we evaluated the additive information of isotopes based on NEON site conditions via a simple linear regression analysis (Fig. 4). We showed that the additive information that *δ13C* provides about *LH* is influenced by mean annual precipitation, aridity, and site elevation (Fig. 4d), as indicated by a significant slope value from the linear regression. *δ13C* is likely to provide more useful information about *LH* in locations with higher atmospheric evaporative demand relative to precipitation, or in locations with less annual precipitation or with higher altitude. The additive information *δ2H* provides about *NEE* was shown to be mainly influenced by the site mean annual temperature (Fig. 4b). *δ2H* tends to be more informative about *NEE* in locations with cooler climates. Similarly, there is more opportunity for *δ2H* to provide additional knowledge about *LH* at locations with cooler climates or less mean annual precipitation (Fig. 4e). No significant relationship was found between the additional information of the *d* provided to either *NEE* or *LH*.

Variations in additional information across NEON sites indicate differences in conditional dependencies of ecosystem fluxes on processes related to isotope fluxes. Changes in ecosystem structure and climate affect the ecosystem's adaptability to environmental changes (Weiskopf *et al* 2020) that influences the biochemical processes responsible for isotope fractionation, which can intensify or weaken these conditional dependencies. It’s worth noting that this study primarily examined how each isotope contributes additional information to *NEE* and *LH* with an emphasis on atmospheric centric conditions. However, it is crucial to acknowledge that ecosystems broadly have a wide range of inherent complexities, such as geomorphology (e.g., slope, aspect) subsurface dynamics (e.g., depth to water table), vegetation species and traits (e.g. plant hydraulic traits), and soil physics (e.g., soil texture), which might play a role in shaping the way of how isotope observations provide extra information about *NEE* and *LH*.

One of key motivations for measuring stable isotopes of water and carbon fluxes is that they may provide unique and novel knowledge about key mechanisms across ecosystems (Good *et al* 2014, Conrad *et al* 2012, Wang *et al* 2010). Such hypothesis has not been formally tested until this study. This is because the flux isotope ratios are influenced by distinct biophysical processes, and thus larger amounts of new mutual information between isotopes and environmental fluxes quantifies the conditions under which these processes are more dominant components of overall bulk fluxes. In this light, the trends described above (and in Fig. 4) are consistent with prior knowledge of isotope geophysics. For instance, equilibrium fractionation factors are sensitive to temperature, particularly at low values (Bowen and Good 2015), with broad decreases in vapor *δ2H* observed poleward at continental scales (Good *et al* 2015). Similarly, evaporation is expected to play a larger role in *LH* fluxes under low vegetation, more arid climates (Wang *et al* 2014) , and this study provides a new way to quantify the relative importance of these isotope processes on bulk fluxes.

It is important to acknowledge that our analysis focused on how daily isotope datasets are informative of bulk ecosystem fluxes. It might be worthwhile to analyze how similar observations are informative of ecosystem fluxes at finer temporal scales. For instance, how lags in isotope dataset responses are influenced by ecosystem processes, and correspondingly how do the partial information components change with different lag timescales can possibly reveal more detailed linkages between ecosystem fluxes and isotope fluxes. In this study, we considered abiotic variables (*VPD*, *T*, *u*, *Rg*) as the confounding part in the partial information decomposition. It might also be worthwhile to explore how other biotic variables such as ecosystem structure, species composition, plant hydraulic traits, and rooting depth can influence the total additive information of isotope dataset to the bulk fluxes.

This analysis is based on current available data products and quality control methods. As more NEON data becomes available, future studies may investigate if and how the results vary with longer time series data and a wider range of environmental conditions. However, given the power of isotopes for tackling fundamental problems in carbon and water cycling and projecting the future of terrestrial ecosystem function under a rapidly changing climate (Bowen and Good 2015, Bowling *et al* 2008), our results can be useful to provide guidance for improving model results after the incorporation of isotope flux ratios.

**Acknowledgements**

The authors want to acknowledge the funding support of the United States National Science Foundation (DEB1802885 and DEB1802880). RPF also received support from the Laboratory Directed Research and Development program of Los Alamos National Laboratory under project number 20210961PRD3.

**Author contribution**

BL and SPG designed the study. RPF provided flux datasets and gap-filled meteorological datasets and wrote part of the data processing steps in Supplementary material. BL analyzed the data and wrote the manuscript. SPG, RPF, CEF, GJB, DCN, CJS, and WRLA reviewed the manuscript.

**Data availability statement**

The datasets that are associated with this study is publicly available at <https://data.neonscience.org/> and https://www.hydroshare.org/resource/e74edc35d45441579d51286ea01b519f/. All materials associated with this study are available at <https://github.com/libonancaesar/ERL_info_isotope>

**Competing interest statement**

The authors declare no conflicts of interest.

**References**

Baldocchi D 2014 Measuring fluxes of trace gases and energy between ecosystems and the atmosphere - the state and future of the eddy covariance method *Glob Chang Biol* **20** 3600–9 Online: https://onlinelibrary.wiley.com/doi/10.1111/gcb.12649

Barnett D T, Adler P B, Chemel B R, Duffy P A, Enquist B J, Grace J B, Harrison S, Peet R K, Schimel D S, Stohlgren T J and Vellend M 2019 The plant diversity sampling design for The National Ecological Observatory Network *Ecosphere* **10** Online: https://onlinelibrary.wiley.com/doi/10.1002/ecs2.2603

Berkelhammer M, Hu J, Bailey A, Noone D C, Still C J, Barnard H, Gochis D, Hsiao G S, Rahn T and Turnipseed A 2013 The nocturnal water cycle in an open-canopy forest *Journal of Geophysical Research: Atmospheres* **118** 10,225-10,242 Online: http://doi.wiley.com/10.1002/jgrd.50701

Bowen G J and Good S P 2015 Incorporating water isoscapes in hydrological and water resource investigations *WIREs Water* **2** 107–19 Online: https://onlinelibrary.wiley.com/doi/10.1002/wat2.1069

Bowling D R, Pataki D E and Randerson J T 2008 Carbon isotopes in terrestrial ecosystem pools and CO 2 fluxes *New Phytologist* **178** 24–40 Online: https://onlinelibrary.wiley.com/doi/10.1111/j.1469-8137.2007.02342.x

Chen J, Wen J, Kang S, Meng X, Tian H, Ma X and Yuan Y 2020 Assessments of the factors controlling latent heat flux and the coupling degree between an alpine wetland and the atmosphere on the Qinghai-Tibetan Plateau in summer *Atmos Res* **240** 104937 Online: https://linkinghub.elsevier.com/retrieve/pii/S016980951931573X

Clausius R 1850 Ueber die bewegende Kraft der Wärme und die Gesetze, welche sich daraus für die Wärmelehre selbst ableiten lassen *Annalen der Physik und Chemie* **155** 500–24 Online: https://onlinelibrary.wiley.com/doi/10.1002/andp.18501550403

Conrad R, Klose M, Yuan Q, Lu Y and Chidthaisong A 2012 Stable carbon isotope fractionation, carbon flux partitioning and priming effects in anoxic soils during methanogenic degradation of straw and soil organic matter *Soil Biol Biochem* **49** 193–9 Online: https://linkinghub.elsevier.com/retrieve/pii/S0038071712000958

Cosgrove B A, Lohmann D, Mitchell K E, Houser P R, Wood E F, Schaake J C, Robock A, Marshall C, Sheffield J, Duan Q, Luo L, Higgins R W, Pinker R T, Tarpley J D and Meng J 2003 Real‐time and retrospective forcing in the North American Land Data Assimilation System (NLDAS) project *Journal of Geophysical Research: Atmospheres* **108** 2002JD003118 Online: https://onlinelibrary.wiley.com/doi/abs/10.1029/2002JD003118

Cover T M and Thomas J A 2005 *Elements of Information Theory* (Wiley) Online: https://onlinelibrary.wiley.com/doi/book/10.1002/047174882X

Dansgaard W 1964 Stable isotopes in precipitation *Tellus A: Dynamic Meteorology and Oceanography* **16** 436–68

Dubbert M and Werner C 2019 Water fluxes mediated by vegetation: emerging isotopic insights at the soil and atmosphere interfaces *New Phytologist* **221** 1754–63 Online: https://onlinelibrary.wiley.com/doi/10.1111/nph.15547

Finkenbiner C E, Li B, Spencer L, Butler Z, Haagsma M, Fiorella R P, Allen S T, Anderegg W, Still C J, Noone D, Bowen G J and Good S P 2022 The NEON Daily Isotopic Composition of Environmental Exchanges Dataset *Sci Data* **9** 353 Online: https://www.nature.com/articles/s41597-022-01412-4

Fiorella R P, Good S P, Allen S T, Guo J S, Still C J, Noone D C, Anderegg W R L, Florian C R, Luo H, Pingintha‐Durden N and Bowen G J 2021 Calibration Strategies for Detecting Macroscale Patterns in NEON Atmospheric Carbon Isotope Observations *J Geophys Res Biogeosci* **126**

Fisher R A and Koven C D 2020 Perspectives on the Future of Land Surface Models and the Challenges of Representing Complex Terrestrial Systems *J Adv Model Earth Syst* **12** Online: https://onlinelibrary.wiley.com/doi/10.1029/2018MS001453

Gemery P A, Trolier M and White J W C 1996 Oxygen isotope exchange between carbon dioxide and water following atmospheric sampling using glass flasks *Journal of Geophysical Research: Atmospheres* **101** 14415–20

Gong W, Gupta H V., Yang D, Sricharan K and Hero A O 2013 Estimating epistemic and aleatory uncertainties during hydrologic modeling: An information theoretic approach *Water Resour Res* **49** 2253–73 Online: http://doi.wiley.com/10.1002/wrcr.20161

Good S P, Noone D, Kurita N, Benetti M and Bowen G J 2015 D/H isotope ratios in the global hydrologic cycle *Geophys Res Lett* **42** 5042–50 Online: http://doi.wiley.com/10.1002/2015GL064117

Good S P, Soderberg K, Guan K, King E G, Scanlon T M and Caylor K K 2014 δ 2 H isotopic flux partitioning of evapotranspiration over a grass field following a water pulse and subsequent dry down *Water Resour Res* **50** 1410–32 Online: http://doi.wiley.com/10.1002/2013WR014333

Goodwell A E and Kumar P 2017 Temporal information partitioning: Characterizing synergy, uniqueness, and redundancy in interacting environmental variables *Water Resour Res* **53** 5920–42 Online: https://onlinelibrary.wiley.com/doi/10.1002/2016WR020216

Goodwell A E, Kumar P, Fellows A W and Flerchinger G N 2018 Dynamic process connectivity explains ecohydrologic responses to rainfall pulses and drought *Proceedings of the National Academy of Sciences* **115** Online: https://pnas.org/doi/full/10.1073/pnas.1800236115

Grossiord C, Buckley T N, Cernusak L A, Novick K A, Poulter B, Siegwolf R T W, Sperry J S and McDowell N G 2020 Plant responses to rising vapor pressure deficit *New Phytologist* **226** 1550–66 Online: https://onlinelibrary.wiley.com/doi/10.1111/nph.16485

Gu L, Meyers T, Pallardy S G, Hanson P J, Yang B, Heuer M, Hosman K P, Riggs J S, Sluss D and Wullschleger S D 2006 Direct and indirect effects of atmospheric conditions and soil moisture on surface energy partitioning revealed by a prolonged drought at a temperate forest site *J Geophys Res* **111** D16102 Online: http://doi.wiley.com/10.1029/2006JD007161

Guan K, Berry J A, Zhang Y, Joiner J, Guanter L, Badgley G and Lobell D B 2016 Improving the monitoring of crop productivity using spaceborne solar‐induced fluorescence *Glob Chang Biol* **22** 716–26 Online: https://onlinelibrary.wiley.com/doi/10.1111/gcb.13136

Jia Z, Liu S, Xu Z, Chen Y and Zhu M 2012 Validation of remotely sensed evapotranspiration over the Hai River Basin, China *Journal of Geophysical Research: Atmospheres* **117** n/a-n/a Online: http://doi.wiley.com/10.1029/2011JD017037

Jung M, Reichstein M, Margolis H A, Cescatti A, Richardson A D, Arain M A, Arneth A, Bernhofer C, Bonal D, Chen J, Gianelle D, Gobron N, Kiely G, Kutsch W, Lasslop G, Law B E, Lindroth A, Merbold L, Montagnani L, Moors E J, Papale D, Sottocornola M, Vaccari F and Williams C 2011 Global patterns of land-atmosphere fluxes of carbon dioxide, latent heat, and sensible heat derived from eddy covariance, satellite, and meteorological observations *J Geophys Res* **116** G00J07 Online: http://doi.wiley.com/10.1029/2010JG001566

Lee S-C, Christen A, Black T A, Jassal R S, Ketler R and Nesic Z 2020 Partitioning of net ecosystem exchange into photosynthesis and respiration using continuous stable isotope measurements in a Pacific Northwest Douglas-fir forest ecosystem *Agric For Meteorol* **292–293** 108109 Online: https://linkinghub.elsevier.com/retrieve/pii/S0168192320302112

Li B and Good S P 2021 Information-based uncertainty decomposition in dual-channel microwave remote sensing of soil moisture *Hydrol Earth Syst Sci* **25** 5029–45 Online: https://hess.copernicus.org/articles/25/5029/2021/

Li S, Kang S, Li F and Zhang L 2008 Evapotranspiration and crop coefficient of spring maize with plastic mulch using eddy covariance in northwest China *Agric Water Manag* **95** 1214–22 Online: https://linkinghub.elsevier.com/retrieve/pii/S0378377408001169

Liu X and Zhang D 2013 Trend analysis of reference evapotranspiration in Northwest China: The roles of changing wind speed and surface air temperature *Hydrol Process* **27** 3941–8 Online: https://onlinelibrary.wiley.com/doi/10.1002/hyp.9527

Lupascu M, Akhtar H, Smith T E L and Sukri R S 2020 Post‐fire carbon dynamics in the tropical peat swamp forests of Brunei reveal long‐term elevated CH 4 flux *Glob Chang Biol* **26** 5125–45 Online: https://onlinelibrary.wiley.com/doi/10.1111/gcb.15195

National Ecological Observatory Network (NEON) 2022a Bundled data products - eddy covariance (DP4.00200.001) Online: https://data.neonscience.org

National Ecological Observatory Network (NEON) 2022b Relative humidity (DP1.00098.001) Online: https://data.neonscience.org

Niu S, Luo Y, Fei S, Yuan W, Schimel D, Law B E, Ammann C, Altaf Arain M, Arneth A, Aubinet M, Barr A, Beringer J, Bernhofer C, Andrew Black T, Buchmann N, Cescatti A, Chen J, Davis K J, Dellwik E, Desai A R, Etzold S, Francois L, Gianelle D, Gielen B, Goldstein A, Groenendijk M, Gu L, Hanan N, Helfter C, Hirano T, Hollinger D Y, Jones M B, Kiely G, Kolb T E, Kutsch W L, Lafleur P, Lawrence D M, Li L, Lindroth A, Litvak M, Loustau D, Lund M, Marek M, Martin T A, Matteucci G, Migliavacca M, Montagnani L, Moors E, William Munger J, Noormets A, Oechel W, Olejnik J, U K T P, Pilegaard K, Rambal S, Raschi A, Scott R L, Seufert G, Spano D, Stoy P, Sutton M A, Varlagin A, Vesala T, Weng E, Wohlfahrt G, Yang B, Zhang Z and Zhou X 2012 Thermal optimality of net ecosystem exchange of carbon dioxide and underlying mechanisms *New Phytologist* **194** 775–83 Online: https://onlinelibrary.wiley.com/doi/10.1111/j.1469-8137.2012.04095.x

Orlowski N, Breuer L, Angeli N, Boeckx P, Brumbt C, Cook C S, Dubbert M, Dyckmans J, Gallagher B, Gralher B, Herbstritt B, Hervé-Fernández P, Hissler C, Koeniger P, Legout A, Macdonald C J, Oyarzún C, Redelstein R, Seidler C, Siegwolf R, Stumpp C, Thomsen S, Weiler M, Werner C and McDonnell J J 2018 Inter-laboratory comparison of cryogenic water extraction systems for stable isotope analysis of soil water *Hydrol Earth Syst Sci* **22** 3619–37

Papale D, Reichstein M, Aubinet M, Canfora E, Bernhofer C, Kutsch W, Longdoz B, Rambal S, Valentini R, Vesala T and Yakir D 2006 Towards a standardized processing of Net Ecosystem Exchange measured with eddy covariance technique: algorithms and uncertainty estimation *Biogeosciences* **3** 571–83 Online: https://bg.copernicus.org/articles/3/571/2006/

Piao S, Wang X, Wang K, Li X, Bastos A, Canadell J G, Ciais P, Friedlingstein P and Sitch S 2020 Interannual variation of terrestrial carbon cycle: Issues and perspectives *Glob Chang Biol* **26** 300–18 Online: https://onlinelibrary.wiley.com/doi/10.1111/gcb.14884

Reichstein M, Falge E, Baldocchi D, Papale D, Aubinet M, Berbigier P, Bernhofer C, Buchmann N, Gilmanov T, Granier A, Grunwald T, Havrankova K, Ilvesniemi H, Janous D, Knohl A, Laurila T, Lohila A, Loustau D, Matteucci G, Meyers T, Miglietta F, Ourcival J-M, Pumpanen J, Rambal S, Rotenberg E, Sanz M, Tenhunen J, Seufert G, Vaccari F, Vesala T, Yakir D and Valentini R 2005 On the separation of net ecosystem exchange into assimilation and ecosystem respiration: review and improved algorithm *Glob Chang Biol* **11** 1424–39 Online: https://onlinelibrary.wiley.com/doi/10.1111/j.1365-2486.2005.001002.x

Rodell M, Houser P R, Jambor U, Gottschalck J, Mitchell K, Meng C-J, Arsenault K, Cosgrove B, Radakovich J, Bosilovich M, Entin J K, Walker J P, Lohmann D and Toll D 2004 The Global Land Data Assimilation System *Bull Am Meteorol Soc* **85** 381–94 Online: https://journals.ametsoc.org/doi/10.1175/BAMS-85-3-381

Ruddell B L, Drewry D T and Nearing G S 2019 Information Theory for Model Diagnostics: Structural Error is Indicated by Trade‐Off Between Functional and Predictive Performance *Water Resour Res* **55** 6534–54 Online: https://onlinelibrary.wiley.com/doi/10.1029/2018WR023692

Safa B, Arkebauer T J, Zhu Q, Suyker A and Irmak S 2019 Net Ecosystem Exchange (NEE) simulation in maize using artificial neural networks *IFAC Journal of Systems and Control* **7** 100036 Online: https://linkinghub.elsevier.com/retrieve/pii/S2468601817302584

Schimel D and Schneider F D 2019 Flux towers in the sky: global ecology from space *New Phytologist* **224** 570–84 Online: https://onlinelibrary.wiley.com/doi/10.1111/nph.15934

Silverman B W 2018 *Density Estimation for Statistics and Data Analysis* (Routledge) Online: https://www.taylorfrancis.com/books/9781351456173

Still C J, Rastogi B, Page G F M, Griffith D M, Sibley A, Schulze M, Hawkins L, Pau S, Detto M and Helliker B R 2021 Imaging canopy temperature: shedding (thermal) light on ecosystem processes *New Phytologist* **230** 1746–53 Online: https://onlinelibrary.wiley.com/doi/10.1111/nph.17321

Su Z 2002 The Surface Energy Balance System (SEBS) for estimation of turbulent heat fluxes *Hydrol Earth Syst Sci* **6** 85–100 Online: https://hess.copernicus.org/articles/6/85/2002/

Talsma C, Good S, Miralles D, Fisher J, Martens B, Jimenez C and Purdy A 2018 Sensitivity of Evapotranspiration Components in Remote Sensing-Based Models *Remote Sens (Basel)* **10** 1601 Online: http://www.mdpi.com/2072-4292/10/10/1601

Tong B, Guo J, Xu H, Wang Y, Li H, Bian L, Zhang J and Zhou S 2022 Effects of soil moisture, net radiation, and atmospheric vapor pressure deficit on surface evaporation fraction at a semi-arid grass site *Science of The Total Environment* **849** 157890 Online: https://linkinghub.elsevier.com/retrieve/pii/S0048969722049890

URycki D R, Bassiouni M, Good S P, Crump B C and Li B 2022 The streamwater microbiome encodes hydrologic data across scales *Science of The Total Environment* **849** 157911 Online: https://linkinghub.elsevier.com/retrieve/pii/S0048969722050100

Veroustraete F, Patyn J and Myneni R B 1996 Estimating net ecosystem exchange of carbon using the normalized difference vegetation index and an ecosystem model *Remote Sens Environ* **58** 115–30 Online: https://linkinghub.elsevier.com/retrieve/pii/0034425795002588

Wang L, Caylor K K, Villegas J C, Barron-Gafford G A, Breshears D D and Huxman T E 2010 Partitioning evapotranspiration across gradients of woody plant cover: Assessment of a stable isotope technique *Geophys Res Lett* **37** n/a-n/a Online: http://doi.wiley.com/10.1029/2010GL043228

Wang L, Good S P and Caylor K K 2014 Global synthesis of vegetation control on evapotranspiration partitioning *Geophys Res Lett* **41** 6753–7 Online: http://doi.wiley.com/10.1002/2014GL061439

Wang P, Li D, Liao W, Rigden A and Wang W 2019 Contrasting Evaporative Responses of Ecosystems to Heatwaves Traced to the Opposing Roles of Vapor Pressure Deficit and Surface Resistance *Water Resour Res* **55** 4550–63 Online: https://onlinelibrary.wiley.com/doi/10.1029/2019WR024771

Weiskopf S R, Rubenstein M A, Crozier L G, Gaichas S, Griffis R, Halofsky J E, Hyde K J W, Morelli T L, Morisette J T, Muñoz R C, Pershing A J, Peterson D L, Poudel R, Staudinger M D, Sutton-Grier A E, Thompson L, Vose J, Weltzin J F and Whyte K P 2020 Climate change effects on biodiversity, ecosystems, ecosystem services, and natural resource management in the United States *Science of The Total Environment* **733** 137782

Whelan M E, Lennartz S T, Gimeno T E, Wehr R, Wohlfahrt G, Wang Y, Kooijmans L M J, Hilton T W, Belviso S, Peylin P, Commane R, Sun W, Chen H, Kuai L, Mammarella I, Maseyk K, Berkelhammer M, Li K-F, Yakir D, Zumkehr A, Katayama Y, Ogée J, Spielmann F M, Kitz F, Rastogi B, Kesselmeier J, Marshall J, Erkkilä K-M, Wingate L, Meredith L K, He W, Bunk R, Launois T, Vesala T, Schmidt J A, Fichot C G, Seibt U, Saleska S, Saltzman E S, Montzka S A, Berry J A and Campbell J E 2018 Reviews and syntheses: Carbonyl sulfide as a multi-scale tracer for carbon and water cycles *Biogeosciences* **15** 3625–57 Online: https://bg.copernicus.org/articles/15/3625/2018/

Wibral M, Priesemann V, Kay J W, Lizier J T and Phillips W A 2017 Partial information decomposition as a unified approach to the specification of neural goal functions *Brain Cogn* **112** 25–38 Online: https://linkinghub.elsevier.com/retrieve/pii/S027826261530021X

Williams M, Richardson A D, Reichstein M, Stoy P C, Peylin P, Verbeeck H, Carvalhais N, Jung M, Hollinger D Y, Kattge J, Leuning R, Luo Y, Tomelleri E, Trudinger C M and Wang Y-P 2009 Improving land surface models with FLUXNET data *Biogeosciences* **6** 1341–59 Online: https://bg.copernicus.org/articles/6/1341/2009/

Williams P L and Beer R D 2010 Nonnegative Decomposition of Multivariate Information Online: http://arxiv.org/abs/1004.2515

Wood D A 2021 Net ecosystem carbon exchange prediction and insightful data mining with an optimized data-matching algorithm *Ecol Indic* **124** 107426 Online: https://linkinghub.elsevier.com/retrieve/pii/S1470160X21000911

Wutzler T, Lucas-Moffat A, Migliavacca M, Knauer J, Sickel K, Šigut L, Menzer O and Reichstein M 2018 Basic and extensible post-processing of eddy covariance flux data with REddyProc *Biogeosciences* **15** 5015–30 Online: https://bg.copernicus.org/articles/15/5015/2018/

Xiao W, Wei Z and Wen X 2018 Evapotranspiration partitioning at the ecosystem scale using the stable isotope method—A review *Agric For Meteorol* **263** 346–61 Online: https://linkinghub.elsevier.com/retrieve/pii/S0168192318303009

Yang Y, Cui Y, Bai K, Luo T, Dai J, Wang W and Luo Y 2019 Short-term forecasting of daily reference evapotranspiration using the reduced-set Penman-Monteith model and public weather forecasts *Agric Water Manag* **211** 70–80 Online: https://linkinghub.elsevier.com/retrieve/pii/S0378377418314732

Yetemen O, Istanbulluoglu E, Flores-Cervantes J H, Vivoni E R and Bras R L 2015 Ecohydrologic role of solar radiation on landscape evolution *Water Resour Res* **51** 1127–57 Online: http://doi.wiley.com/10.1002/2014WR016169

Yusup Y and Liu H 2020 Effects of persistent wind speeds on turbulent fluxes in the water-atmosphere interface *Theor Appl Climatol* **140** 313–25 Online: http://link.springer.com/10.1007/s00704-019-03084-4

Zeng S, Xia J, Chen X, Zou L, Du H and She D 2020 Integrated land-surface hydrological and biogeochemical processes in simulating water, energy and carbon fluxes over two different ecosystems *J Hydrol (Amst)* **582** 124390 Online: https://linkinghub.elsevier.com/retrieve/pii/S0022169419311254

Zhao W L, Qiu G Y, Xiong Y J, Paw U K T, Gentine P and Chen B Y 2020 Uncertainties Caused by Resistances in Evapotranspiration Estimation Using High-Density Eddy Covariance Measurements *J Hydrometeorol* **21** 1349–65 Online: <https://journals.ametsoc.org/view/journals/hydr/21/6/JHM-D-19-0191.1.xml>

Zhou S, Yu B, Zhang Y, Huang Y and Wang G 2018 Water use efficiency and evapotranspiration partitioning for three typical ecosystems in the Heihe River Basin, northwestern China *Agric For Meteorol* **253–254** 261–73 Online: https://linkinghub.elsevier.com/retrieve/pii/S016819231830039X

A graph of different colored squares

Description automatically generated

**Figure 1** (a) Individual mutual information, *I*(X;Y), shared between net ecosystem exchange, *NEE,* and each individual meteorologicalvariable (vapor pressure deficit, *VPD*, air temperature, *T*, global radiation, *Rg*, windspeed, *u*). (b) Individual information shared between latent heat flux, *LH,* and each individual meteorological variable. Boxes of mutual information between meteorological variables and flux are consists of the same quantity that is calculated based on different isotope availability (e.g., box of *I*(*VPD*; *NEE*) consists of *I*(*VPD*; *NEE*) based on the availability of *δ13C*, *I*(*VPD*; *NEE*) based on the availability of *δ2H*, and *I*(*VPD*; *NEE*) on the availability of *d*, collectively). The mean and median values of each boxplot are shown as black triangle and white line, respectively. The double asterisk indicates a significant p-value (<0.01).

**A graph of a graph

Description automatically generated**

**Figure 2** (a)The unique information, *U*, synergistic information, *S*, and redundant information, *R*, of the *δ13C, δ2H,* and *d* stable isotope flux ratios on the net ecosystem exchange, *NEE,* and (b) latent heat flux, *LH*. The values of *S*,and *R* are calculated by averaging across different meteorological variables, indicated by **Y** (e.g., the average over *S*(*δ2H*,*VPD*;*LH*), *S*(*δ2H*,*T*;*LH*), *S*(*δ2H*,*u*;*LH*), and *S*(*δ2H*,*Rg*;*LH*) for *S*). The mean and median values of each boxplot are shown as black triangle and white line, respectively. The double asterisk indicates a significant p-value (<0.01).

**A map of the world

Description automatically generated**

**Figure 3** The additive information of (a) *δ13C*, (b) *δ2H*, and (c) *d* isotope data about net ecosystem exchange, *NEE.* Theadditive information of (d) *δ13C*, (e) *δ2H*, and (f) *d* isotope data about latent heat flux, *LH*.The additive information is the sum unique, *U,* and synergistic, *S,* information added by each data source.

**Graphical user interface, chart, application, scatter chart

Description automatically generated**

**Figure 4** The total added information of (a) *δ*13*C*, (b) *δ2H*, and (c) *d* isotope data about net ecosystem exchange, *NEE,* against scaled site-specific variables. The total added information of (d) *δ*13*C*, (e) *δ2H*, and (f) *d* isotope data about latent heat flux, *LH* against scaled site-specific variables. Solid lines indicate a significant p-values (< 0.05) of the slopes.