Ecohydrology

WILEY

RESEARCH ARTICLE OPEN ACCESS

Enhancing Representativeness of Eddy Covariance Evapotranspiration With Remote Sensing and In Situ Data: A Case Study in the Brazilian Cerrado

Alex N. A. Kobayashi[1,2] | Jamil A. A. Anache[1] | Jullian S. Sone[3] | Gabriela C. Gesualdo[4] | Dimaghi Schwamback[1,5] | Edson Wendland[1]

[1]Department of Hydraulics and Sanitation, São Carlos School of Engineering at the University of São Paulo, São Paulo, Brazil | [2]The Centre for Hydrogeology and Geothermics (CHYN), University of Neuchâtel, Neuchâtel, Switzerland | [3]Department of Economics, University of Waterloo, Waterloo, Ontario, Canada | [4]Department of Geosciences, Pennsylvania State University, University Park, Pennsylvania, USA | [5]Division of Water Resources Engineering, Lund University, Skåne, Sweden

Correspondence: Jamil A. A. Anache (jamil.anache@usp.br)

Received: 19 June 2024 | **Revised:** 16 January 2025 | **Accepted:** 21 February 2025

Funding: This study was financially supported by the Coordination for the Improvement of Higher Education Personnel (CAPES, Finance Code 001), the Brazilian National Council for Scientific and Technological Development (CNPq) and the São Paulo Research Foundation (FAPESP, grant numbers 2015/03806-1, 2019/24292-7 and 2021/14016-2).

Keywords: eddy covariance technique | enhanced vegetation index (EVI) | flux footprint | water and energy fluxes

ABSTRACT

The Cerrado *sensu stricto*, so-called wooded Cerrado, is one of the many phytophysiognomies of the undisturbed Brazilian Cerrado ecoregion holding a biodiversity hotspot towards an extensive area. Thus, such land is under constant land use and cover changes mainly due to the demand for agriculture land, sector with the highest consumption of available freshwater in this ecoregion. This underscores this region's critical economic and environmental relevance. The evapotranspiration (ET) in the Brazilian Cerrado is a major player in the regional hydrological cycle, significantly influencing rainfall distribution in this ecoregion. Nonetheless, acquiring observed measurements of ET measurements using the eddy covariance (EC) technique is still challenging, especially where the flux footprint represents a heterogeneous canopy. Thus, how vegetation and spatiotemporal climate variability affect EC evapotranspiration were assessed in a preserved fragment of wooded Cerrado. Our goals were to (i) improve the water fluxes representativeness by coupling flux footprint with remote sensing products to account for spatiotemporal variability and (ii) assess how seasonal variability of vegetation and climate affect water fluxes in this study's target vegetation. First, we determined which integration approach with enhanced vegetation index (EVI) improved the representativeness of the study's site target vegetation—either a half-hourly flux footprint integration or a fixed-extent radius surrounding the flux tower. We further conducted a random forest analysis to identify the most relevant environmental and meteorological variables influencing the canopy conductance. We noted a significant gain in performance when EVI is integrated with the half-hourly footprint, indicating an improvement in the representativeness between this remote sensing variable and the EC fluxes, evidenced by a better energy balance closure. And we found that the most relevant variables were the vapor pressure deficit and soil water content at a seasonal and annual basis, respectively. Our findings highlight that integrating a vegetation index with flux footprint can enhance spatiotemporal representativeness of the target vegetation, contributing to a better regional understanding of not only the wooded Cerrado but also other complex and heterogeneous land covers in terms of water and energy fluxes.

1 | Introduction

Evapotranspiration (ET) is a key component of the hydrological cycle, and an in-depth understanding of its processes is critical to sustainably managing water resources, especially in the agriculture sector (Sun et al. 2019; Baldocchi 2020). Nonetheless, the ET quantification is still a challenge given the difficulty of integrating micro-scale processes—for example, water transport through soil pores and plant xylem—into a framework that can describe regional patterns (Katul and Novick 2009). Commonly, global ET is estimated using mass conservation approaches lacking site-specific monitoring and modeling (Wang and Dickinson 2012). Eddy covariance (EC) flux towers are potential instruments to obtain in situ and stand-scale measurements and energy partitioning with negligible interference (Baldocchi and Ryu 2011). The EC method is a direct method and has the advantage of integrating spatial heterogeneity through the flux footprint, that is, the area that contributes to the flux at each time-step (Schmid 2002). Direct measurements using EC are complex tasks due to the need for specialized and expensive equipment, along with special care in sampling. This complexity hinders the availability of long time series and its popularization. To overcome this challenge the FLUXNET was created as a 'global network of regional networks', composed of nearly two decades of meteorological observations (Baldocchi et al. 2001; Pastorello et al. 2020). These data are extremely important to understand ecosystem functioning, trends in climate, greenhouse gases and air pollution. However, data acquisition and processing to uncover spatial and temporal variations of global ecosystem function need to be an ongoing effort, especially in a variety of ecosystems. For instance, dryland ecosystems in the Western United States and Australia share similar climate characteristics but have very distinct ecosystem responses to climate variability. Nevertheless, evapotranspiration is processed with uniform vegetation assumption, causing biases in both regions (Huang et al. 2021).

Ground-based studies have decreased over the last years despite their importance for a fundamental understanding of ecosystem functioning in different regions of the globe. To mention, Burt and McDonnell (2015) reported a decline in field observations of runoff all over the world. The understanding of nuances in hydrological processes becomes more challenging, where empirical studies are scarce (i.e., Southern hemisphere). Then, have we observed enough through empirical studies to enable the use and improve the reliability of models? The answer would be definitely no for South America. Melo et al. (2020) found that Brazil has a very low number of in situ hydrological monitoring of ET, a scenario where time series from 32 monitoring basins are 12-year long, on average. This finding is particularly concerning when considering ET a major component of the water budget. At the same time, Melo et al. (2021) evaluated remote sensing evapotranspiration models across South America and highlighted the challenge of validating their results due to scale incompatibility and the great site-specific heterogeneity. In addition, the authors emphasize the paramount importance of expanding the flux tower network in the continent. Indeed, there is a need to promote long-term field-based studies to understand their places' idiosyncrasies, as well as to support practitioners with tools and approaches using process-based knowledge of hydrological applications in data-sparse regions (Blöschl et al. 2013).

The flux footprint modeling is a technique used to overcome the main source of bias and uncertainties in EC measures, which is the assumption of flux homogeneity (Chu et al. 2021). It is based on the transfer function between the measured value and the set of forcing on the surface-atmosphere interface, taking into account that at a heterogeneous surface the measured value will depend on which part of the surface the sensor has the most substantial influence (Schmid 2002). In the flux footprint modeling, Earth system models (ESMs) are commonly used although the main challenge to their application is to deal with the spatiotemporal mismatch between footprint spatial scale and that of most ESMs (Xu et al. 2020). Even though recent progress has been made in this regard (Brombacher et al. 2022; Chu et al. 2021), there is still the need to investigate the relationship between land surface characteristics and evapotranspiration at a finer spatial and temporal resolution, along with the assessment of the representativeness of the target ecosystem. Furthermore, to pursue an assessment of spatiotemporal variability of evapotranspiration at a broader scale, variables measured using flux towers should be integrated with high-resolution satellite data (Baldocchi 2020). Interpreting these results across representative flux footprints must be ensured.

Considering these gaps, this study aims to assess how vegetation heterogeneity and seasonal variability affect observed evapotranspiration in the Cerrado *sensu stricto*. We focus on the challenges regarding the direct use of half-hourly footprint since aggregate footprints from many time steeps smooth the variable and extreme footprint (Chu et al. 2021) and the matching spatial and temporal scales between flux and remote-sensing data. This paper explores a coupling technique to integrate remote sensing products into EC flux footprint and hence improve the representativeness of EC fluxes by accounting for spatiotemporal variability in the target vegetation. We also assess how seasonality and climate variability help explain source heterogeneity in the Cerrado *sensu stricto*.

2 | Material and Methods

This study was developed following four steps depicted in Figure 1. Observed micrometeorological data were preprocessed and integrated with Landsat images to investigate how heterogeneity and seasonal variation of the studied vegetation influence evapotranspiration. We also compared the performance of a footprint-weighted Enhanced Vegetation Index ($EVI_{footprint}$) with another common approach that assumes a fixed radius around the meteorological tower (EVI_{radius}). Lastly, to identify and rank the most important variables influencing evapotranspiration, we carried out a random forest analysis using biophysical variables representing atmospheric and phenological conditions. In the next subsections, we provide further details of the experimental setup and methodological steps taken in this study.

2.1 | Site Description and Vegetation Characteristics

This study site was conducted in a undisturbed fragment of Cerrado *sensu stricto* with 3.3 km^2 at the Arruda Botelho Institute (IAB) in Itirapina, a municipality of the state of São Paulo, Brazil (Figure 2a). The climate is classified as humid subtropical (Cwa) according to the Köppen-Geiger

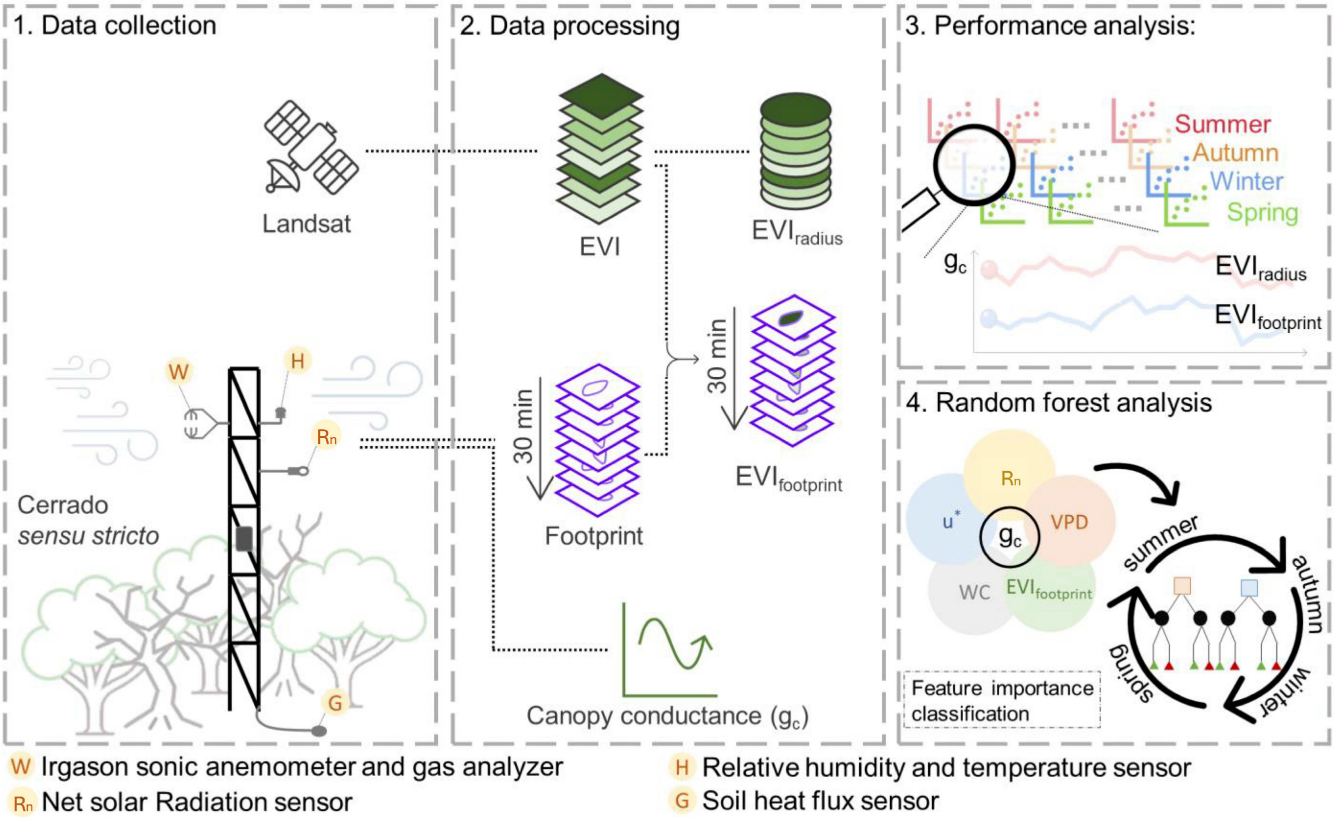

FIGURE 1 | Study design for this study: (1) in situ data collection with an array of sensors and remote sensing data, (2) data processing for the enhanced vegetation index (EVI) and canopy conductance, (3) performance analysis with correlation and (4) seasonal random forest analysis using the feature importance classification explaining canopy conductance (g_c) based on friction velocity (u^*), net solar radiation (R_n), vapor pressure deficit (VPD) and the footprint-weighted EVI ($EVI_{footprint}$).

classification system (Peel et al. 2007), characterized by hot and wet period, which mostly comprises spring and summer (October to March); and dry period, which mostly includes autumn and winter (April to September). The four seasons are defined as follows: summer spans from December 22 to March 20, autumn from March 20 to June 21, winter from June 21 to September 22/23, and spring from September 22/23 to December 22. The mean annual observed precipitation between 1979 and 2014 was 1486 mm, with a mean temperature of 21.6°C and relative humidity of 71% (Cabrera et al. 2016) (Figure 2b).

Cerrado *sensu stricto*, also known and referred hereafter as wooded Cerrado, is one of the several physiognomies within the Cerrado Ecoregion, Brazil's second-largest ecoregion encompassing 2,033,601 km^2. This physiognomy consists of a mosaic of more than 4000 small, tortuous, 6–7 m high tree species (Alberton et al. 2014). Most of these tree species have a thick cork on their trunks, stiff leathery leaves, and xeromorphic characteristic (Ribeiro and Walter 2008). Wooded Cerrado vegetation supports a high density of shrub and tree species, including common species such as *Bauhinia rufa*, *Xylopia Aromatica*, *Miconia Rubiginosa*, *Virola sebifera* and *Myrcia guianensis* (Reys et al. 2013). About 190 species are included in the study site flora, and 107 (56.3%) are dispersed by animals (Camargo et al. 2013). The vegetation presents a seasonal behavior (Alberton et al. 2014), with its canopy greenness varying according to the rainfall occurrence and other climatic variables and presenting a higher dispersion in comparison to lower canopies found in Cerrado ecoregion (Alberton et al. 2017). Since the mid-20th century, the Cerrado ecoregion has undergone agricultural expansion (mainly cattle pastures and cash crops) leading to a loss of almost 50% of its native forest vegetation (Strassburg et al. 2017), including the wooded Cerrado. Consequently, this ecoregion is one of the 25 global biodiversity hotspots (Myers et al. 2000).

2.2 | Experimental Setup and Data Processing

A meteorological tower (lat: −22.1710, long: −47.8710) was installed in a well-preserved remaining area of wooded Cerrado (Figures 1 and 2) and is listed in the Ameriflux network under the ID BR-IAB (https://ameriflux.lbl.gov/sites/siteinfo/BR-IAB). Micrometeorological variables and air fluxes were monitored using low and high-frequency instrumentation (Table 1) installed at a 16-m height in a monitoring tower. Two soil heat flux plates (HFP-01) were also installed near the monitoring tower, as depicted in Figure 1. We corrected the observed evapotranspiration—that is, latent heat flux—carrying out the following steps: (i) adjustment of the anemometer's orientation using planar fit regression (Wilczak et al. 2001); (ii) temperature correction using Schotanus, Nieuwstadt e De Bruin (SND) (Schotanus et al. 1983) and adding Webb-Pearnman-Leuning (WPL) terms (Webb et al. 1980); (iii) correction of low- and high-frequency spectrum using Moncrieff et al. (1997) and Massman (2000), respectively;

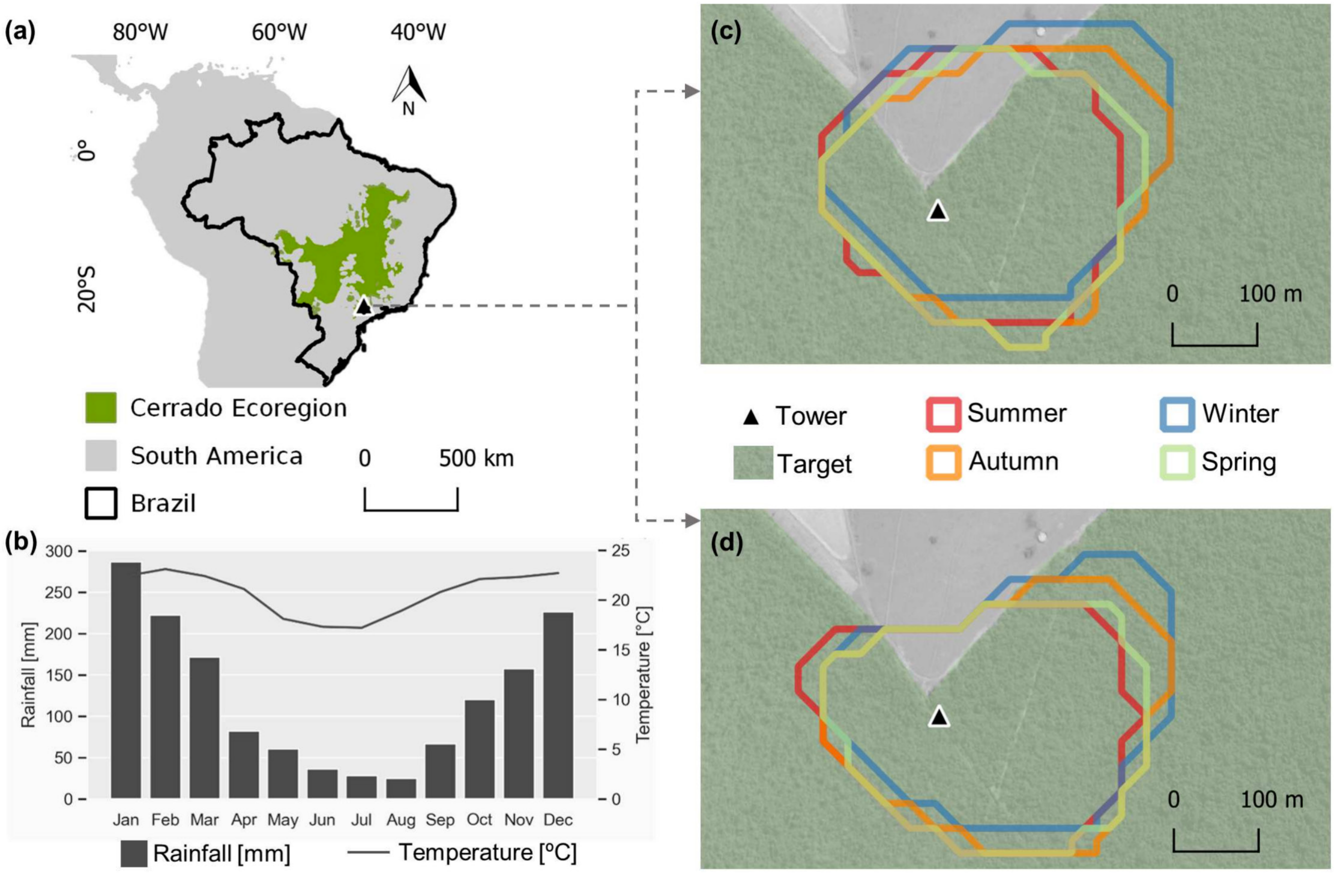

FIGURE 2 | (a) Study site regional context in South America, (b) mean monthly rainfall (bars) and temperature (line), (c) non-filtered flux footprint and (d) filtered flux footprint for different seasons.

TABLE 1 | Sensors characteristics for the variables monitored in the study site.

Variable	Sensor	Height	Measurement range	Maximum error
Temperature [°C]	HMP155A	16	−80°C to 60°C	±0.45°C
Relative humidity [%]	HMP155A	16	0%–100%	±1.7%
Rainfall [mm]	Hydrological Services TB4	16	0–700 mm h^{-1}	±3%
Atmospheric pressure [mbar]	Vaisala CS106	16	500–1100 mbar	±1.5 mbar
Wind speed [m s^{-1}]	Irgasson sonic anemometer	16	0–30 m s^{-1}	±1.8 m s^{-1}
Wind direction [°]	Irgasson sonic anemometer	16	0–360°	±0.7°
H_2O molar fraction [mmol mol^{-1}]	Irgasson gas analyzer	16	0–72 mmol mol^{-1}	2%
Soil water content [%]	FDR EnvironSCAN Sentek	−0.5[a]	0%–65%	±3%
Net solar radiation [W m^{-2}]	Kipp & Zonen CNR4	10	±2000 W m^{-2}	±20 W m^{-2}
Soil heat flux [W m^{-2}]	Hukseflux HFP01	−0.1[a]	±2000 W m^{-2}	−15 to 5%

[a]Negative values correspond to depths below the ground level.

(iv) data quality control using tests steady state (Foken and Wichura 1996; Vickers and Mahrt 1997) and turbulent conditions (Kaimal and Finnigan 1994; Foken and Wichura 1996; Aubinet et al. 2012).

A footprint-based filter was employed on each time interval of our time series to improve data quality further and ensure representativeness by identifying and excluding data from non-target areas. To ensure fluxes are from the target area (i.e., wooded Cerrado), footprint was firstly calculated using a two-dimensional model (Kljun et al. 2015) at a 30-min time interval and then normalized as in Equation (1). We also defined a pixel threshold to limit the area to be analyzed. To do so, reprojection was required to bring the footprint data to a 30-m spatial resolution since each pixel contribution is highly influenced by its resolution. This specific resolution was adopted to meet that of remote sensing products used in this study, detailed in the Section 2.3. Then, an acceptance rate was computed by integrating the footprint and the land cover (LC) (Equation 2), so that the observed data is filtered based on an acceptance threshold of 80% of the cumulative contribution of the target LC.

$$f_{norm}(x,y) = \frac{f(x,y)}{\iint_{area} f(x,y)dxdy} \tag{1}$$

$$f_{accept} = \iint_{area} LC(x,y) \odot f_{norm}(x,y)dxdy \tag{2}$$

Checking for surface energy balance is a common practice for quality control in studies using EC flux measurements, which are often unable to close a balance equation over forests (Wilson et al. 2002). This is mainly due to larger available energy at the surface, net radiation (R_n) minus soil surface heat flux (G_0), than the turbulent fluxes, sensible and latent heat fluxes ($H+LE$) (Foken and Oncley 1995). One of the main reasons behind this lack of experimental balance closure is related to uncertainties in post-field data processing (Malhi et al. 2004; Massman and Lee 2002). Although it is not our objective to investigate the sources of these uncertainties, we demonstrate how using footprint-filtered data provides a slightly better surface energy balance closure compared with a balance using all data available.

The decoupling factor (Ω, Equation 3) was computed using filtered data after the quality control check to better understand surface biophysical controls over actual evapotranspiration (AET). This dimensionless coefficient estimates the degree of atmosphere-vegetation interaction, ranging from 0 to 1 (Jarvis and Mcnaughton 1986). At the lower limit of Ω, the canopy is strongly coupled with the surrounding atmospheric conditions; otherwise, the canopy is considered decoupled from the free air stream.

$$\Omega = \frac{AET}{PET} = \frac{1+\frac{\Delta}{\gamma}}{1+\frac{\Delta}{\gamma}+\frac{g_a}{g_c}} \tag{3}$$

where Δ [kPa°C^{-1}] is the slope for saturation vapor pressure curve, γ [kPa°C^{-1}] is the psychrometric constant, g_a[ms^{-1}] is the aerodynamic conductance as in Gash et al. (1999) (Equation 4) and g_c[ms^{-1}] is the canopy conductance calculated using the inverted Penman-Monteith (Monteith 1981) (Equation 5).

$$g_a = \frac{u^{*2}}{u} \tag{4}$$

$$g_c = \frac{\gamma \lambda ET g_a}{\Delta(R_n - G) + \rho_a c_p VPD g_a - \lambda(\Delta+\gamma)ET} \tag{5}$$

where u[ms^{-1}] is the wind speed measured using the triaxial sonic anemometer, u^*[ms^{-1}] is the friction velocity, which represents the relationship of the vertical flux of horizontal momentum measured near the surface (Stull 1988; Gash et al. 1999), ρ_a[kgm^{-3}] is the density of dry air, c_p[MJkg^{-1}°C^{-1}], VPD[kPa] is the atmospheric vapor pressure deficit, R_n[Wm^{-2}] is the net radiation and G[Wm^{-2}] is the soil heat flux.

2.3 | Improving Representativeness of EC Fluxes

To better understand the effects of the spatial heterogeneity of vegetation on water flux response, enhanced vegetation indices (EVIs) were derived from the 30-m Landsat images with a 16-day revisit cycle. The seasonal variation of $\text{EVI}_{\text{radius}}$ and $\text{EVI}_{\text{footprint}}$ can be observed in Figure 3.

We adopted EVI for its sensitivity in high biomass regions, while reducing the atmospheric influences Huete et al. (2002). In this study, we linearly interpolated the Landsat series 7 ETM+ and 8 with atmospheric corrections for surface reflectance (USGS level 2, collection 2 and tier 1) to improve temporal resolution. We adopted two approaches to compare the seasonal performance in the correlation between vegetation index and canopy conductance (g_c, Equation 5), which physically represents the fluxes transportation from the canopy to the atmosphere (Peng et al. 2019). One approach relies on assuming a fixed 2-km radius around the study site ($\text{EVI}_{\text{radius}}$) while the other integrates EVI with the footprint for each 30-min time interval ($\text{EVI}_{\text{footprint}}$, Equation 6). To avoid introducing more uncertainty by gap-filling the data, we compared both products on a 30-min time scale. Both approaches indicate that the footprint is asymmetrically distributed around the monitoring tower due to prevailing wind direction (Figure 2c), especially in the winter.

$$EVI_{footprint} = \iint_{area} EVI(x,y) \odot f(x,y)dxdy \tag{6}$$

Thus, we performed an hourly Pearson's correlation analysis for each season, comparing both $\text{EVI}_{\text{radius}}$ (median) and $\text{EVI}_{\text{footprint}}$ (weighted) with g_c. This approach allowed us to assess whether the phenology of vegetation is better represented using filtered flux data within this methodology.

To rank relevant variables influencing the estimated fluxes, hydro-meteorological and phenological variables were used in regressor trees of the Random Forest (RF) algorithm (Denisko and Hoffman 2018). The canopy conductance (g_c) was adopted as the response variable (target) since it represents the water fluxes from roots to the canopy surface (Peng et al. 2019). Explanatory variables used in the RF were the net solar radiation (Rn), friction velocity (u^*), atmospheric vapor pressure deficit (VPD), soil water content (SWC), and the $\text{EVI}_{\text{footprint}}$ (Equation 6). We considered footprint-filtered and non-filtered data to test how the flux homogeneity assumption affects the importance feature in the RF regression.

The permutation feature importance is computed as the decrease in the model score when a single variable value is randomly shuffled (Breiman 2001; Pedregosa et al. 2011). The technique has the advantage of indicating the decency of the model on the variables, despite the relationship between the variables and the target, making it possible for different

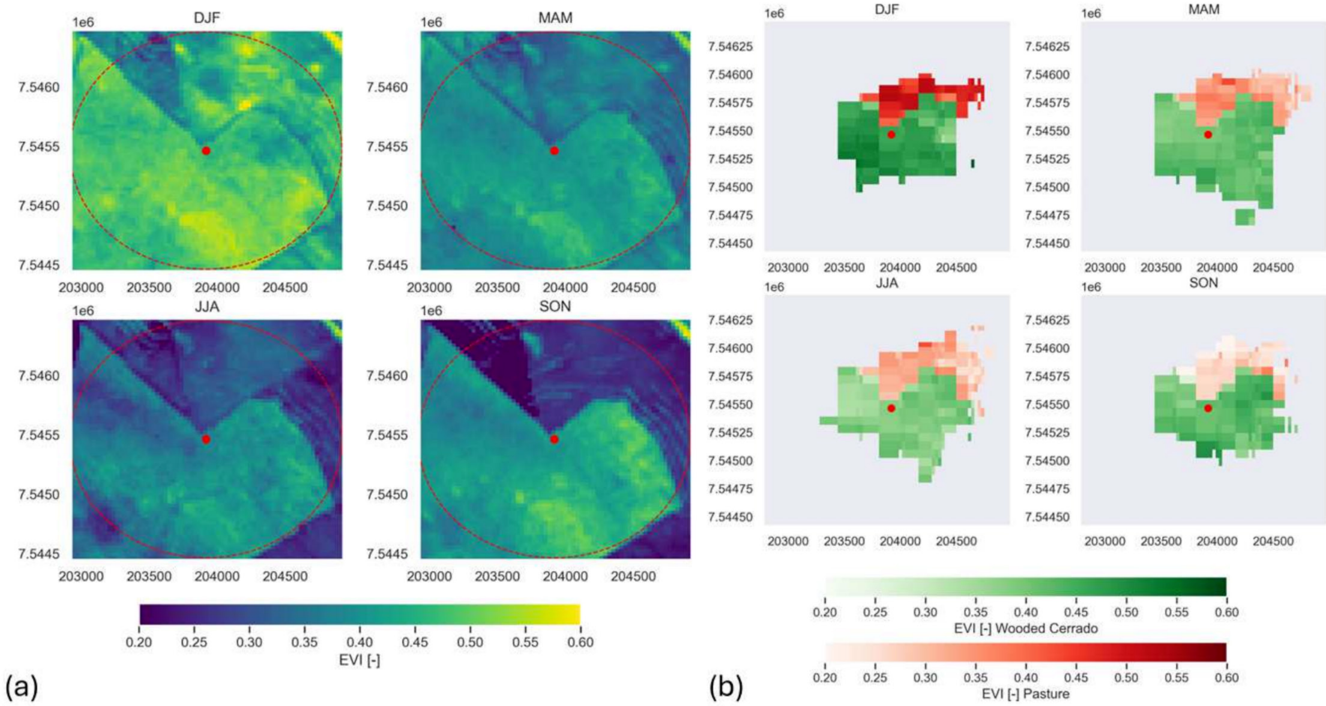

FIGURE 3 | Study site EVI seasonal maps around the meteorological tower (red dot) for (a) fixed radius and (b) filtered flux footprint areas, where green areas represent EVI values from accepted flux sources (valid contributions to the flux), while red areas correspond to rejected flux sources (excluded from flux analysis), where DJF means December, January and February (Summer); MAM means March, April and May (Autumn); JJA means June, July and August (Winter); and SON means September, October and November (Spring).

permutations of the same variable. Here, we analyzed the variable importance according to season and the footprint filter applied. The intent was to understand how each variable contributed and shifted in its importance throughout the year by comparing filtered and non-filtered data. We also applied a 10-fold permutation to these variables to reduce high carnality bias. All analyses were carried out by using a Python script (Kobayashi 2022).

3 | Results

We assessed the energy balance and noted a slight improvement in the energy closure when using the footprint filter (Figure 4). The slope changed from 0.68 when using all available data to 0.72 when filtering the data with the footprint. Although we could not define the measurement error, we hypothesize that this improvement in the energy balance was due to a better representation of the vicinity area's heterogeneity captured by the footprint filter.

Regarding filtered data, the canopy conductance (g_c) and decoupling factor (Ω) presented different density shapes but similar behavior for each season (Figure 5). In general, we noted a more dispersed shape of g_c around its mean value than that of Ω, especially during the winter and spring. This is due to a constant oscillation between sequential days with water and solar radiation surplus and deficit affecting g_c while the atmosphere is coupled to the vegetation (average Ω of 0.14). Despite showing differences in their density curves, both variables records decreased from the summer to the spring corroborating that the most coupled

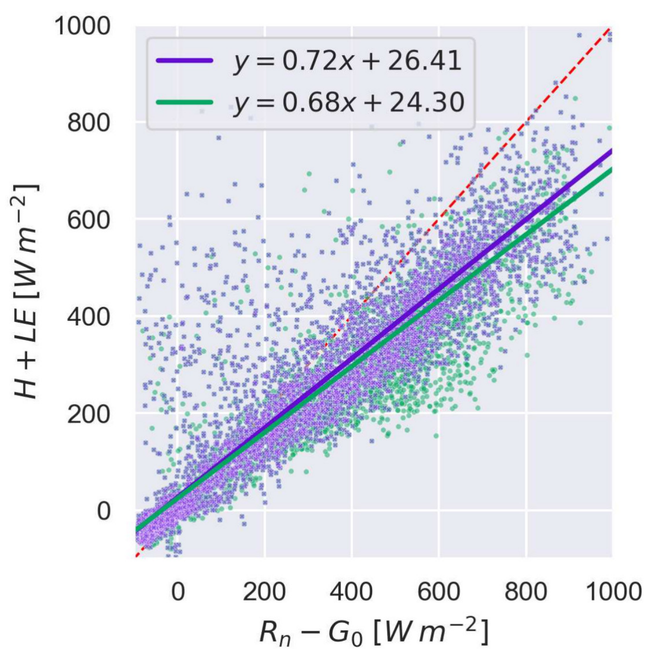

FIGURE 4 | Energy balance for all data available (green) and data filtered by footprint (purple).

period occurs during more water-limited seasons (i.e., winter and spring). On the other hand, the maximum mean Ω (0.31) was observed during the summer when vegetation in the target area is more decoupled from the atmospheric conditions: evapotranspiration is driven by radiation as VPD is primarily low due to frequent rainfalls (Figure 2).

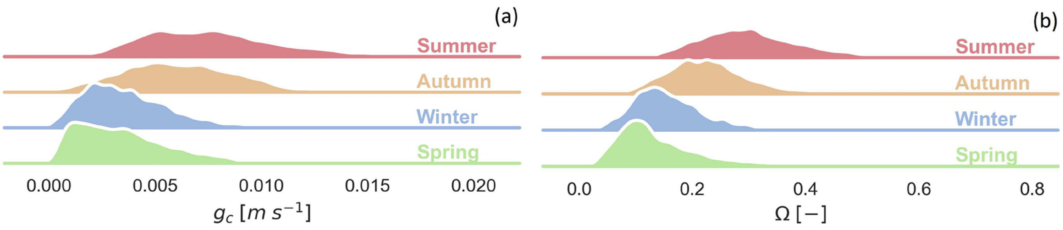

FIGURE 5 | Density function for all seasons for (a) canopy conductance (gc) and (b) decoupling factor (Ω) of the wooded Cerrado using filtered data.

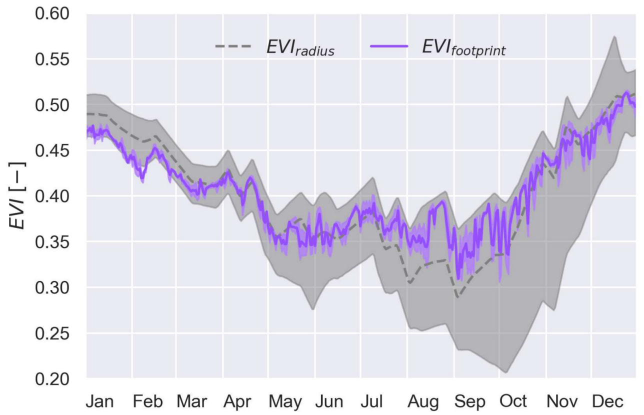

FIGURE 6 | Annual vairation in median EVI_{radius} and $EVI_{footprint}$. The gray and purple shaded areas represent the range of the lower and upper quantile for the EVI_{radius} and $EVI_{footprint}$, respectively.

3.1 | Improved Representativeness of Eddy Covariance Fluxes Using Footprint-Weighted EVI

We evaluated the effects of using a footprint-weighted EVI ($EVI_{footprint}$) and a median value of EVI considering a fixed 2-km radius surrounding the monitoring tower (EVI_{radius}). The median values of EVI_{radius} range from 0.50 in the rainy season to 0.25 at the end of the dry season (September) (Figure 6). The $EVI_{footprint}$ and EVI_{radius} are alike during the rainy season while diverging during the dry season (June to November). During drier months, the $EVI_{footprint}$ reached the lowest value of nearly 0.30. In terms of interquartile range, the difference between the two approaches may be due to the cumulative daily footprint fetch of 80% used to obtain the $EVI_{footprint}$, compared with the arbitrary area adopted in the EVI_{radius}. When adopting an arbitrary radius surrounding the monitoring tower, we contemplate vegetation indices from surrounding land covers (e.g., pastureland in dark gray in Figure 2) other than indices from wooded Cerrado.

We evaluated the hourly g_c across all seasons considering the radius and footprint-weighted approaches to compare their seasonal performance (Figure 7). The first aspect noted is how the transition periods between wet and dry seasons (Autumn and Spring) have high correlation values throughout the day. Also, there is a consistent increase in correlation when utilizing $EVI_{footprint}$ against EVI_{radius}, except during the summer. In the Winter, the correlation between EVI and g_c reaches nearly 100%. On the other hand, the correlation significantly varies along the day during the summer, with a correlation increase in the morning followed by a sharp decline after midday. Still, the maximum correlation for the summer months peaked at 0.4, indicating a moderate correlation.

3.2 | Key Influencing Factors to Eddy Covariance Fluxes

We conducted a random forest analysis using footprint-filtered and non-filtered data to identify the most important variables to canopy conductance (g_c). We used four hydro-meteorological variables and the $EVI_{footprint}$. When contrasting filtered and non-filtered data, we observed significant changes in the relative importance of the explaining variables (Table 2). The most evident changes were observed in the $EVI_{footprint}$ and R_n. The importance of the $EVI_{footprint}$ to predict g_c was lower using the footprint-filtered data. On the other hand, the importance of R_n increased when using filtered data, showing higher importance throughout the seasons. This decrease in the importance of the $EVI_{footprint}$ underscores the efficiency of the footprint filter. By using non-filtered data, the RF algorithm attributes the data variability to the phenological variable when splitting the nodes based on the $EVI_{footprint}$. We also highlight the relatively higher importance of the $EVI_{footprint}$ during the autumn and spring, which indicates that the heterogeneity of the vegetation is still playing a role in predicting g_c as those are transition seasons to dry-wet periods.

When focusing only on filtered data, the overall explanatory performance of each variable changed throughout the seasons (Table 2). In the summer, the most relevant variable related to g_c is R_n (RF = 0.31) and VPD (RF = 0.29). In the autumn, R_n (RF = 0.26) continued as the leading variable while the rest of the variables shared almost the same relevance (around 0.20), except SWC (RF = 0.10). The VPD was the most important variable explaining g_c during the winter (RF = 0.38) and spring (RF = 0.43). During the spring, R_n (RF = 0.20) was not among the two most relevant variables related to canopy conductance as $EVI_{footprint}$ (RF = 0.27) was the second most important variable. Lastly, the SWC (RF = 0.35) was highlighted as the most important variable related to g_c when analyzing the overall performance of the variables in all seasons.

4 | Discussion

In most studies, the vegetation homogeneity assumption is violated compromising data quality and analysis even in some regional-scale studies (e.g., Heinsch et al. 2006; Rodrigues

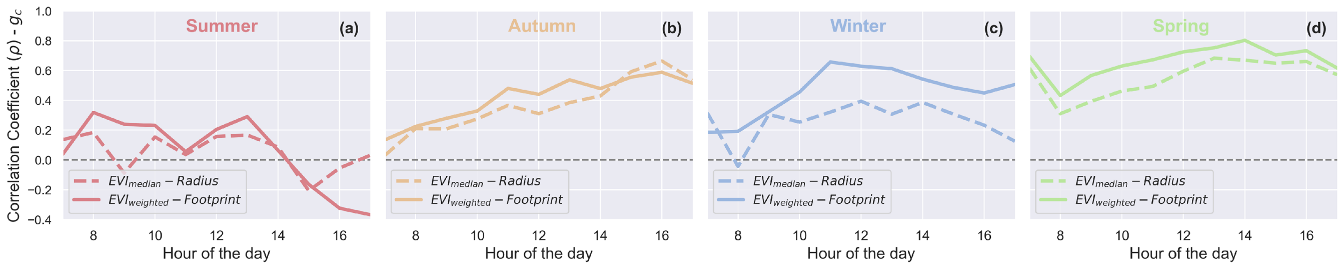

FIGURE 7 | Hourly EVI correlation by season for EVI_{radius} (dashed line) and $EVI_{footprint}$ (solid line).

TABLE 2 | Random forest feature importance by season and by footprint filter.

	VPD		SWC		u^*		R_n		$EVI_{footprint}$	
Season	**Non-filtered**	**Filtered**	**Non-filtered**	**Filtered**	**Non-filtered**	**Filtered**	**Non-filtered**	**Filtered**	**Non-filtered**	**Filtered**
Summer	0.21	0.29	0.22	0.15	0.22	0.16	0.15	0.31	0.19	0.09
Autumn	0.08	0.22	0.07	0.10	0.23	0.22	0.16	0.26	0.46	0.19
Winter	0.39	0.38	0.08	0.10	0.07	0.09	0.32	0.40	0.15	0.03
Spring	0.36	0.43	0.01	0.03	0.13	0.08	0.08	0.20	0.43	0.27
All seasons	0.26	0.24	0.32	0.35	0.11	0.11	0.18	0.21	0.13	0.09

et al. 2014). In this study, we investigated how vegetation heterogeneity and seasonal variability affected evapotranspiration and found that using a footprint-filtered EVI improved the spatial representativeness of the target area. When comparing the interquartile range of the footprint-weighted and fixed-extent EVI ($EVI_{footprint}$ and EVI_{radius}), the latter presented a wider range encompassing other vegetation than the wooded Cerrado while $EVI_{footprint}$ is more correlated with the canopy conductance (g_c). The bias stemmed from a footprint-to-target-area mismatch is also a remaining gap we explore here by using half-hourly footprint to better understand the seasonal influence of vegetation on evapotranspiration. This is one of the six research opportunities identified by Chu et al. (2021) to address critical gaps in the representativeness of EC flux footprint. Our findings reveal the potential improvement of spatial representativeness by using an index integrating vegetation and footprint to deal with spatiotemporal heterogeneity.

Despite the enhancement in energy balance closure due to filtering of the footprint flux data (Figure 4), the statistical regression of turbulent energy fluxes (sensible and latent heat) against available energy (net radiation, less soil heat flux) showed a lower slope value compared to the global FLUXNET average (Wilson et al. 2002; Stoy et al. 2013). However, the study site is a heterogeneous and patchy landscape, with contrasting land covers within the footprint, and the slope value agrees with other studies in similar conditions (deciduous broadleaf forests, mixed forests and wetlands, ranging between 0.70 and 0.78) (Stoy et al. 2013). This addresses a site limitation for flux measurements, and in a further monitoring period the level of heterogeneity of the site should be reduced (find a more homogeneous fetch), and also reduce uncertainties regarding net radiation measurements, biological energy assimilation, and storage terms (Stoy et al. 2013).

The identified most important factors influencing seasonal variations in g_c and Ω (decoupling factor) corroborate other studies in the wooded Cerrado (Cabral et al. 2015; Giambelluca et al. 2009; Blanken and Black 2004). For instance, vapor pressure deficit (VPD) was consistently one of the most important variables for predicting g_c mainly in the drier seasons due to a higher daily amplitude and higher coupling between canopy and atmosphere. However, in the annual analysis, soil water content (SWC) became the most important variable due to its amplitude. The variance of this variable was insignificant when splitting the observations per season and not correlated with g_c variation. Seasonally, we were unable to provide a detailed explanation about the influence of SWC on g_c due to uncertainties regarding root zone depth in wooded Cerrado areas and the lack of SWC monitoring in deeper positions in our study site (Alberton et al. 2014; Canadell et al. 1996). We only monitored SWC at 0.5 m depth, characterizing a caveat in our seasonal analysis of this variable importance.

The u^* (friction velocity) presented a significant importance for the wet seasons, which corroborates with Hong et al. (2014) when observing a dependency between the ratio of actual and potential ET and u^* under wet conditions. Nevertheless, regarding the dry season and the annual analysis, its importance was significantly reduced. Consequently, we found no clear evidence that u^* was correlated with g_c, except for their correlation due to the daily variance of u^* and its relation to atmospheric stability. In contrast, the high performance of the R_n (net solar radiation) in terms of RF importance was expected (Giambelluca et al. 2009; Cabral et al. 2015) since adding energy to the vegetation systems increases cellular respiration capacity. Furthermore, the consistent increase in R_n importance when using only filtered data indicates an improvement in representativeness of the target vegetation, which is related directly to the latent heat flux and its capacity of energy closure (Figure 4), represented by g_c.

The interaction between EVI and g_c can also be understood through the lens of stomatal conductance, which is a major component of g_c. Stomatal conductance varies diurnally and seasonally in response to environmental factors such as VPD and R_n, which are also captured by EVI (Gowdy et al. 2022; Bai et al. 2015). During periods of high solar radiation and low air-humidity, stomatal conductance typically increases leading to higher rates of transpiration and hence photosynthesis, which are reflected in elevated EVI values. Conversely, stomatal closure reduces g_c under drought conditions and, consequently, contributes to a decline in EVI due to plant stress (Bai et al. 2015). Camargo et al. (2018) provided a long-term study in the wooded Cerrado near our study site, in which they observed a peak in leaf fall during the dry season and in leaf growth during the dry-to-wet transition period over 106 species of tropical trees (deciduous and semi-deciduous). These behaviors are reflected in our results in the RF importance of EVI values in the fall and winter seasons and are consistent with other studies that utilized LAI (Vourlitis et al. 2002; Giambelluca et al. 2009). One study (Rodrigues et al. 2014), in particular, for a mix of forest and grassland using a MODIS product, their EVI results are comparable in terms of range and pattern of value with our results for EVI_{radius}. These corroborated results reflect the fact that our study site can be categorized as medium representative (Göckede et al. 2008) if no filter or integration with the footprint is applied. By integrating EVI with the footprint, we were able to filter non-target areas and better correlate it with g_c. Nonetheless, after filtering data, there was still significant heterogeneity of species that differs from each other in terms of leafing patterns (Almeida et al. 2014; Alberton et al. 2014), which were observed in the EVI and the evapotranspiration response.

As mentioned before, complex EC measurement sites can influence the representativeness of evapotranspiration measurements, and such complexity in the land use surrounding the instruments tower was the main scientific endeavor faced by this study. Such difficulties raised the main scientific questions discussed here and also opened the path for new discussions based on the limitations found along the way. It is worth mentioning that it is not possible to use a single EC tower measurement data to infer the regional evapotranspiration of the entire Cerrado ecoregion (Olson et al. 2001). The footprint-weighted EVI may not be representative of the ecoregion as it comprises different phytophysiognomies and vegetation densities: from open fields to woodlands and forests (Eiten 1978). Thus, this study comprises data that represents a typical woodland of the Cerrado uplands.

Although EC flux measurements over wooded and tall canopies—likewise the land cover observed through the weighed footprint—are a widely used technique, some complementary assessments along the site and in the data set may be necessary for further studies to better understand net ecosystem exchange, its components, and main drivers (Longdoz and Granier 2012). Thus, following the need for parallel non-EC ecosystem measurements, the EVI data set was a powerful complement to this research. However, the assessment of the EVI correlation with g_c in summer reached a stronger variability along the day due to the reduced number of EVI sampling points in comparison to other seasons (Figure 7a). This reduced EVI sampling was related to the higher cloud cover of the remote sensing data during the summer period (Prudente et al. 2020), which reduced the number of usable images along the analysis. Consequently, this reduced availability of EVI images may have also affected the random forest analysis. Thus, we recommend that further ground-based measurements or remotely piloted aircraft system (RPAS) for imagery acquisition (Tang and Shao 2015) take place in order to obtain more information about the current status of the target ecosystem when the occurrence of clouds is higher during certain months of the year (e.g., in our case during the summer). This would increase the temporal resolution of remote sensing products when less optical information about the vegetation is available. In addition to RPAS, which can enhance both the spatial and temporal resolutions of vegetation monitoring, deploying a phenological camera at the flux tower presents a more practical alternative (Alberton et al. 2014; Alberton et al. 2017), enabling the continuous acquisition of data that can be seamlessly correlated with other monitored variables.

Concerning further studies involving the dataset assessed here and the EC measurement site, it is expected to (i) expand the flux time-series analysis; (ii) include greenhouse gases EC measurements such as CO_2 to obtain essential responses such as net ecosystem exchange (NEE), gross primary production (GPP), and ecosystem respiration (TER); (iii) use the flux footprint prediction analysis proposed by Kljun et al. (2015) to determine land cover classes contribution based on remote sensed data in order to calibrate NEE models according to the multiple ecosystems (Rößger et al. 2019; Holl et al. 2020) caught by the tower in its heterogeneous and patchy surroundings; (iv) continue studies related to ecosystem hydrology and extract some important responses from the targeted ecosystem such as underlying water use efficiency (WUE) and evapotranspiration partitioning (Zhou et al. 2016).

5 | Conclusions

This paper reflects the first results from an empirical study involving an eddy covariance tower placed within a site containing a complex land cover distribution over its fetch. Thus, a footprint modeling followed by data filtering to select fluxes that better represented a wooded Cerrado vegetation, covering most of the tower surroundings. The results reported here show that integrating vegetation index with flux footprint has the potential to enhance the representativeness of the target vegetation. Our study also uncovers the most important environmental factors driving evapotranspiration along the seasons over a remaining Cerrado vegetation area in Southeast Brazil.

The flux representativeness can be improved by integrating a 30-min flux footprint assessment to filter the data and calculating the decoupling factor (Ω) and canopy conductance (g_c) for the target ecosystem (wooded Cerrado in this case study). This enhancement was observed through a better energy balance closure from an area with a more homogeneous EVI distribution and a better correlation between g_c and EVI along the seasons.

The most important variables explaining g_c varied along the seasons. The SWC regulates g_c at an annual basis, but the atmosphere (represented by VPD) was the most important driver related to how vegetation seasonally regulates evapotranspiration process within the wooded Cerrado. The phenology assessed here by EVI plays a remarkable and variable role along the seasons.

Despite the limitations of this study site, we explored the effects of land surface heterogeneity in the evapotranspiration with the implementation of coupling with footprint. Although flux footprint prediction can be resourcefully expensive, we found its coupling with each 30-min flux added significant value besides the classification of the level of representativeness of our study site. Furthermore, this study aimed to be the foundation of other carbon fluxes and gap-filling applications and extended to other water balance studies concerning the Cerrado ecoregion.

Author Contributions

Alex N. A. Kobayashi: conceptualization, methodology, formal analysis, investigation, visualization, writing – original draft. **Jamil A. A. Anache:** conceptualization, methodology, formal analysis, investigation, visualization, writing – review and editing. **Jullian S. Sone:** methodology, formal analysis, investigation, visualization, writing – review and editing. **Gabriela C. Gesualdo:** formal analysis, investigation, visualization, writing – review and editing. **Dimaghi Schwamback:** investigation, methodology, formal analysis, investigation, visualization, writing – review and editing. **Edson Wendland:** conceptualization, funding acquisition, project administration, writing – review and editing.

Acknowledgements

The authors acknowledge the Graduate Program in Hydraulic Engineering and Sanitation (PPGSHS) at São Carlos School of Engineering, University of São Paulo (EESC/USP), for the scientific support. This study was financially supported by the Coordination for the Improvement of Higher Education Personnel (CAPES, Finance Code 001), the Brazilian National Council for Scientific and Technological Development (CNPq) and the São Paulo Research Foundation (FAPESP, grant numbers 2015/03806-1, 2019/24292-7 and 2021/14016-2). Lastly, the authors would like to acknowledge the Arruda Botelho Institute for facilitating the study area and installations at the São José farm in Itirapina, São Paulo. The Article Processing Charge for the publication of this research was funded by the Coordenação de Aperfeiçoamento de Pessoal de Nível Superior - Brasil (CAPES) (ROR identifier: 00x0ma614).

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The dataset that supports the findings of this study is available at https://doi.org/10.5281/zenodo.7110770#.Yy-gaq3vXFA (Kobayashi 2022). The study site is listed with the ID BR-IAB on the Ameriflux platform (https://ameriflux.lbl.gov/sites/siteinfo/BR-IAB).

References

Alberton, B., J. Almeida, R. Helm, et al. 2014. "Using Phenological Cameras to Track the Green Up in a Cerrado Savanna and Its On-the-Ground Validation." *Ecological Informatics* 19: 62–70. https://linkinghub.elsevier.com/retrieve/pii/S1574954113001325.

Alberton, B., R. S. Torres, L. F. Cancian, et al. 2017. "Introducing Digital Cameras to Monitor Plant Phenology in the Tropics: Applications for Conservation." *Perspectives in Ecology and Conservation* 15, no. 2: 82–90. https://linkinghub.elsevier.com/retrieve/pii/S2530064417300019.

Almeida, J., J. A. dos Santos, B. Alberton, et al. 2014. "Applying Machine Learning Based on Multiscale Classifiers to Detect Remote Phenology Patterns in Cerrado Savanna Trees." *Ecological Informatics* 23: 49–61. https://linkinghub.elsevier.com/retrieve/pii/S1574954113000654.

Aubinet, M., T. Vesala, and D. Papale. 2012. *Eddy Covariance*. 1st ed. Edited by M. Aubinet, T. Vesala, and D. Papale. Springer Netherlands. https://link.springer.com/10.1007/978-94-007-2351-1.

Bai, Y., G. Zhu, Y. Su, et al. 2015. "Hysteresis Loops Between Canopy Conductance of Grapevines and Meteorological Variables in an Oasis Ecosystem." *Agricultural and Forest Meteorology* 214-215: 319–327. https://linkinghub.elsevier.com/retrieve/pii/S0168192315007029.

Baldocchi, D. D. 2020. "How Eddy Covariance Flux Measurements Have Contributed to Our Understanding of Global Change Biology." *Global Change Biology* 26, no. 1: 242–260. https://onlinelibrary.wiley.com/doi/10.1111/gcb.14807.

Baldocchi, D. D., E. Falge, L. Gu, et al. 2001. "FLUXNET: A New Tool to Study the Temporal and Spatial Variability of Ecosystem-Scale Carbon Dioxide, Water Vapor, and Energy Flux Densities." *Bulletin of the American Meteorological Society* 82, no. 11: 2415–2434. https://journals.ametsoc.org/view/journals/bams/82/11/1520-0477_2001_082_2415_fantts_2_3_co_2.xml.

Baldocchi, D. D., and Y. Ryu. 2011. "A Synthesis of Forest Evaporation Fluxes—From Days to Years—As Measured With Eddy Covariance." In *Forest Hydrology and Biogeochemistry: Synthesis of Past Research and Future Directions*, Vol. 216, 101–116. Springer, Dordrecht. https://link.springer.com/10.1007/978-94-007-1363-5_5.

Blöschl, G., M. Sivapalan, T. Wagener, et al. 2013. *Runoff Prediction in Ungauged Basins*. Cambridge University Press. https://www.cambridge.org/core/product/identifier/9781139235761/type/book.

Blanken, P. D., and T. A. Black. 2004. "The Canopy Conductance of a Boreal Aspen Forest, Prince Albert National Park, Canada." *Hydrological Processes* 18, no. 9: 1561–1578. https://onlinelibrary.wiley.com/doi/10.1002/hyp.1406.

Breiman, L. 2001. "Random Forests." *Machine Learning* 45: 5–32.

Brombacher, J., I. R. O. Silva, J. Degen, et al. 2022. "A Novel Evapotranspiration Based Irrigation Quantification Method Using the Hydrological Similar Pixels Algorithm." *Agricultural Water Management* 267: 107602.

Burt, T. P., and J. J. McDonnell. 2015. "Whither Field Hydrology? The Need for Discovery Science and Outrageous Hydrological Hypotheses." *Water Resources Research* 51, no. 8: 5919–5928.

Cabral, O. M. R., H. R. da Rocha, J. H. Gash, et al. 2015. "Water and Energy Fluxes From a Woodland Savanna (Cerrado) in Southeast Brazil." *Journal of Hydrology: Regional Studies* 4: 22–40. https://linkinghub.elsevier.com/retrieve/pii/S2214581815000440.

Cabrera, M. C. M., J. A. A. Anache, C. Youlton, et al. 2016. "Performance of Evaporation Estimation Methods Compared With Standard 20 m^2 Tank." *Revista Brasileira de Engenharia Agrícola e Ambiental* 20, no. 10: 874–879. http://www.scielo.br/scielo.php?script=sci_arttext&pid=S1415-43662016001000874&lng=en&tlng=en.

Camargo, M. G. G., G. H. Carvalho, B. C. Alberton, et al. 2018. "Leafing Patterns and Leaf Exchange Strategies of a Cerrado Woody Community." *Biotropica* 50, no. 3: 442–454.

Camargo, M. G. G., E. Cazetta, H. M. Schaefer, et al. 2013. "Fruit Color and Contrast in Seasonal Habitats—A Case Study From a Cerrado

Savanna." *Oikos* 122, no. 9: 1335–1342. https://onlinelibrary.wiley.com/doi/10.1111/j.1600-0706.2013.00328.x.

Canadell, J., R. B. Jackson, J. R. Ehleringer, et al. 1996. "Maximum Rooting Depth of Vegetation Types at the Global Scale." *Oecologia* 108: 583–595.

Chu, H., X. Luo, Z. Ouyang, et al. 2021. "Representativeness of Eddy-Covariance Flux Footprints for Areas Surrounding AmeriFlux Sites." *Agricultural and Forest Meteorology* 301-302, no. February.

Denisko, D., and M. M. Hoffman. 2018. "Classification and Interaction in Random Forests." *Proceedings of the National Academy of Sciences* 115, no. 8: 1690–1692. https://pnas.org/doi/full/10.1073/pnas.1800256115.

Eiten, G. 1978. "Delimitation of the Cerrado Concept." *Vegetatio* 36, no. 3: 169–178.

Foken, T., and S. Oncley. 1995. "Workshop on Instrumental and Methodical Problems of Land Surface Flux Measurements." *Bulletin of the American Meteorological Society* 76, no. 7: 1191–1224. https://journals.ametsoc.org/doi/10.1175/1520-0477-76.7.1191.

Foken, T., and B. Wichura. 1996. "Tools for Quality Assessment of Surface-Based Flux Measurements." *Agricultural and Forest Meteorology* 78, no. 1-2: 83–105. https://linkinghub.elsevier.com/retrieve/pii/0168192395022481.

Göckede, M., T. Foken, M. Aubinet, et al. 2008. "Quality Control of CarboEurope Flux Data—Part 1: Coupling Footprint Analyses With Flux Data Quality Assessment to Evaluate Sites in Forest Ecosystems." *Biogeosciences* 5, no. 2: 433–450.

Gash, J. H. C., F. Valente, and J. S. David. 1999. "Estimates and Measurements of Evaporation From Wet, Sparse Pine Forest in Portugal." *Agricultural and Forest Meteorology* 94, no. 2: 149–158.

Giambelluca, T. W., F. G. Scholz, S. J. Bucci, et al. 2009. "Evapotranspiration and Energy Balance of Brazilian Savannas With Contrasting Tree Density." *Agricultural and Forest Meteorology*: 1365–1376.

Gowdy, M., P. Pieri, B. Suter, et al. 2022. "Estimating Bulk Stomatal Conductance in Grapevine Canopies." *Frontiers in Plant Science* 13: 839378. https://www.frontiersin.org/articles/10.3389/fpls.2022.839378/full.

Heinsch, F. A., M. Zhao, S. W. Running, et al. 2006. "Evaluation of Remote Sensing Based Terrestrial Productivity From MODIS Using Regional Tower Eddy Flux Network Observations." *IEEE Transactions on Geoscience and Remote Sensing* 44, no. 7: 1908–1923.

Holl, D., E. M. Pfeiffer, and L. Kutzbach. 2020. "Comparison of Eddy Covariance CO_2 and CH_4 Fluxes From Mined and Recently Rewetted Sections in a Northwestern German Cutover Bog." *Biogeosciences* 17, no. 10: 2853–2874.

Hong, J., K. Takagi, T. Ohta, et al. 2014. "Wet Surface Resistance of Forest Canopy in Monsoon Asia: Implications for Eddy-Covariance Measurement of Evapotranspiration." *Hydrological Processes* 28, no. 1: 37–42.

Huang, X., J. Xiao, X. Wang, et al. 2021. "Improving the Global MODIS GPP Model by Optimizing Parameters With FLUXNET Data." *Agricultural and Forest Meteorology* 300: 108314.

Huete, A., K. Didan, T. Miura, et al. 2002. "Overview of the Radiometric and Biophysical Performance of the MODIS Vegetation Indices." *Remote Sensing of Environment* 83, no. 1-2: 195–213.

Jarvis, P. G., and K. G. Mcnaughton. 1986. "Stomatal Control of Transpiration: Scaling Up from Leaf to Region." *Advances in Ecological Research* 15, no. C: 1–49.

Kaimal, J. C., and J. J. Finnigan. 1994. *Atmospheric Boundary Layer Flows: Their Structure and Measurement*. 1st ed. Oxford University Press, Inc.

Katul, G., and K. Novick. 2009. "Evapotranspiration." *Encyclopedia of Inland Waters*: 661–667.

Kljun, N., P. Calanca, M. W. Rotach, et al. 2015. "A Simple Two-Dimensional Parameterisation for Flux Footprint Prediction (FFP)." *Geoscientific Model Development* 8, no. 11: 3695–3713.

Kobayashi, A. N. A. 2022. "Cerrado Water Fluxes Representativeness (v. 1.0.0)." https://doi.org/10.5281/zenodo.7110770#.Yy-gaq3vXFA.

Longdoz, B., and A. Granier. 2012. "Eddy Covariance Measurements Over Forests." In *Eddy Covariance*, 309–318. Springer Netherlands.

Malhi, Y., K. McNaughton, and C. Von Randow. 2004. "Low Frequency Atmospheric Transport and Surface Flux Measurements." In *Handbook of Micrometeorology*, edited by X. Lee, W. Massman, and B. Law, Vol. 29, 101–118. Springer. http://link.springer.com/10.1007/1-4020-2265-4_5.

Massman, W. J. 2000. "A Simple Method for Estimating Frequency Response Corrections for Eddy Covariance Systems." *Agricultural and Forest Meteorology* 104, no. 3: 185–198. https://linkinghub.elsevier.com/retrieve/pii/S0168192300001647.

Massman, W. J., and X. Lee. 2002. "Eddy Covariance Flux Corrections and Uncertainties in Long-Term Studies of Carbon and Energy Exchanges." *Agricultural and Forest Meteorology* 113, no. 1-4: 121–144. https://linkinghub.elsevier.com/retrieve/pii/S0168192302001053.

Melo, D. C. D., J. A. A. Anache, C. N. Almeida, et al. 2020. "The Big Picture of Field Hydrology Studies in Brazil." *Hydrological Sciences Journal* 65, no. 8: 1262–1280. https://www.tandfonline.com/doi/abs/10.1080/02626667.2020.1747618.

Melo, D. C. D., J. A. A. Anache, V. P. Borges, et al. 2021. "Are Remote Sensing Evapotranspiration Models Reliable Across South American Ecoregions?."*Water Resources Research* 57, no. 11.

Moncrieff, J. B., J. M. Massheder, H. De Bruin, et al. 1997. "A System to Measure Surface Fluxes of Momentum, Sensible Heat, Water Vapour and carbon dioxide." *Journal of Hydrology* 188-189, no. 1-4: 589–611.

Monteith, J. L. 1981. "Evaporation and Surface Temperature." *Quarterly Journal of the Royal Meteorological Society* 107, no. 451: 1–27.

Myers, N., R. A. Mittermeier, C. G. Mittermeier, G. A. B. da Fonseca, and J. Kent. 2000. "Biodiversity Hotspots for Conservation Priorities." *Nature* 403, no. 6772: 853–858. http://www.nature.com/articles/35002501.

Olson, D. M., E. Dinerstein, E. D. Wikramanayake, et al. 2001. "Terrestrial Ecoregions of the World: A New Map of Life on Earth."

Pastorello, G., C. Trotta, E. Canfora, et al. 2020. "The FLUXNET2015 Dataset and the ONEFlux Processing Pipeline for Eddy Covariance Data." *Scientific Data 2020 7:1* 7, no. 1: 1–27. https://www.nature.com/articles/s41597-020-0534-3.

Pedregosa, F., G. Varoquaux, A. Gramfort, et al. 2011. "Scikit-Learn: Machine Learning in Python." *Journal of Machine Learning Research* 12: 2825–2830.

Peel, M. C., B. L. Finlayson, and T. A. McMahon. 2007. "Updated World Map of the Köppen-Geiger Climate Classification." *Hydrology and Earth System Sciences* 11, no. 5: 1633–1644.

Peng, L., Z. Zeng, Z. Wei, et al. 2019. "Determinants of the Ratio of Actual to Potential Evapotranspiration." *Global Change Biology* 25, no. 4: 1326–1343. https://onlinelibrary.wiley.com/doi/10.1111/gcb.14577.

Prudente, V. H. R., V. S. Martins, D. C. Vieira, et al. 2020. "Limitations of Cloud Cover for Optical Remote Sensing of Agricultural Areas Across South America." *Remote Sensing Applications: Society and Environment* 20: 100414.

Rößger, N., C. Wille, D. Holl, et al. 2019. "Scaling and Balancing Carbon Dioxide Fluxes in a Heterogeneous Tundra Ecosystem of the Lena River Delta." *Biogeosciences* 16, no. 13: 2591–2615.

Reys, P., M. G. G. Camargo, M. T. Grombone-Guaratini, et al. 2013. "Estrutura e composição florística de um Cerrado sensu stricto e sua importância para propostas de restauração ecológica." *Hoehnea* 40, no. 3: 449–464. http://www.scielo.br/scielo.php?script=sci_arttext&pid=S2236-89062013000300005&lng=pt&tlng=pt.

Ribeiro, J. F., and B. M. T. Walter. 2008. "As Principais Fitofisionomias do Bioma Cerrado." In *Cerrado: Ecologia e Flora v. 2.*, edited by S. M. Sano, S. P. Almeida, and J. F. Ribeiro, 876. EMBRAPA-CERRADOS.

Rodrigues, T. R., G. L. Vourlitis, F. D. A. Lobo, et al. 2014. "Seasonal Variation in Energy Balance and Canopy Conductance for a Tropical Savanna Ecosystem of South Central Mato Grosso, Brazil." *Journal of Geophysical Research: Biogeosciences* 119, no. 1: 1–13.

Schmid, H. P. 2002. "Footprint Modeling for Vegetation Atmosphere Exchange Studies: A Review and Perspective." *Agricultural and Forest Meteorology* 113, no. 1-4: 159–183.

Schotanus, P., F. T. M. Nieuwstadt, and H. A. R. De Bruin. 1983. "Temperature Measurement With a Sonic Anemometer and Its Application to Heat and Moisture Fluxes." *Boundary-Layer Meteorology* 26, no. 1: 81–93.

Stoy, P. C., M. Mauder, T. Foken, et al. 2013. "A Data-Driven Analysis of Energy Balance Closure Across FLUXNET Research Sites: The Role of Landscape Scale Heterogeneity." *Agricultural and Forest Meteorology* 171-172: 137–152. https://linkinghub.elsevier.com/retrieve/pii/S0168192312003413.

Strassburg, B. B. N., T. Brooks, R. Feltran-Barbieri, et al. 2017. "Moment of Truth for the Cerrado Hotspot." *Nature Ecology & Evolution 2017 1:4* 1, no. 4: 1–3. https://www.nature.com/articles/s41559-017-0099.

Stull R. B. 1988. *An Introduction to Boundary Layer Meteorology.* 1st ed. Edited by R. B. Stull. Springer Netherlands. http://link.springer.com/10.1007/978-94-009-3027-8.

Sun, X., B. P. Wilcox, and C. B. Zou. 2019. "Evapotranspiration Partitioning in Dryland Ecosystems: A Global Meta-Analysis of In Situ Studies." *Journal of Hydrology* 576: 123–136.

Tang, L., and G. Shao. 2015. "Drone Remote Sensing for Forestry Research and Practices." *Journal of Forestry Research* 26, no. 4: 791–797.

Vickers, D., and L. Mahrt. 1997. "Quality Control and Flux Sampling Problems for Tower and Aircraft Data." *Journal of Atmospheric and Oceanic Technology* 14, no. 3: 512–526. http://journals.ametsoc.org/doi/10.1175/1520-0426(1997)014%3C0512:QCAFSP%3E2.0.CO;2.

Vourlitis, G. L., N. Priante Filho, M. M. S. Hayashi, et al. 2002. "Seasonal Variations in the Evapotranspiration of a Transitional Tropical Forest of Mato Grosso, Brazil." *Water Resources Research* 38, no. 6: 30–1.

Wang, K., and R. E. Dickinson. 2012. "A Review of Global Terrestrial Evapotranspiration: Observation, Modeling, Climatology, and Climatic Variability." *Reviews of Geophysics* 50, no. 2: 2005. https://doi.org/10.1029/2011RG000373.

Webb, E. K., G. I. Pearman, and R. Leuning. 1980. "Correction of Flux Measurements for Density Effects due to Heat and Water Vapour Transfer." *Quarterly Journal of the Royal Meteorological Society*: 85–100.

Wilczak, J. M., S. P. Oncley, and S. A. Stage. 2001. "Sonic Anemometer Tilt Correction Algorithms." *Boundary-Layer Meteorology* 99, no. 1: 127–150. http://link.springer.com/10.1023/A:1018966204465.

Wilson, K., A. Goldstein, E. Falge, et al. 2002. "Energy Balance Closure at FLUXNET Sites." *Agricultural and Forest Meteorology* 113, no. 1-4: 223–243. https://linkinghub.elsevier.com/retrieve/pii/S0168192302001090.

Xu, K., M. Sühring, S. Metzger, et al. 2020. "Can Data Mining Help Eddy Covariance See the Landscape? A Large-Eddy Simulation Study." *Boundary-Layer Meteorology* 176, no. 1: 85–103. https://link.springer.com/article/10.1007/s10546-020-00513-0.

Zhou, S., B. Yu, Y. Zhang, et al. 2016. "Partitioning Evapotranspiration Based on the Concept of Underlying Water Use Efficiency." *Water Resources Research* 52, no. 2: 1160–1175. http://doi.wiley.com/10.1002/2015WR017766.