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Impacts of Pasture Conversion to Sugarcane on Water Fluxes and Water Use Efficiency in the Southeastern US

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ABSTRACT

The expansion of sugarcane (cane), a high-yielding perennial crop, will likely reshape the bioenergy landscape in the Southeastern US. However, its ecohydrological implications, particularly following conversion from grazed pastures, a dominant land use in the region, remain highly uncertain. We investigated the impact of cane expansion on evapotranspiration (ET) and its partitioning, and the mechanisms influencing both ET components and water use efficiency (WUE) across multiple scales and growth cycles in subtropical Florida. We combined eddy covariance, biometric measurements, and process-based stomatal conductance (g_s) models. ET was 1.7% lower in cane than in improved pasture (IMP) but exceeded that in semi-native pasture (SN) by 21%. Transpiration (T) followed a similar pattern, consistent with lower g_s in cane relative to IMP. Cane had more conservative water use and greater sensitivity of g_s to vapor pressure deficit (VPD) compared to IMP pasture, suggesting cane may be more tolerant of increasing atmospheric water demand. In contrast, SN showed lower g_s and weaker stomatal sensitivity to VPD compared to cane, resulting in lower T. In cane, stomatal regulation and T varied across growth cycles, with stomata becoming less water conservative as stands matured, highlighting the importance of incorporating stand age-dependent stomatal regulation into hydrological models. Evaporation (E) was higher in cane than pastures (19%–26%), partially offsetting WUE gains. Cane exhibited higher intrinsic WUE (GPP/g_s ; Gross Primary Productivity), ecosystem WUE (GPP/ET), and harvest WUE (harvest/ET) than both pasture types. Large-scale pasture-to-cane conversion could produce widely contrasting hydrological outcomes. The net regional impact will depend on the proportion of each pasture type converted and on cane's high g_s sensitivity to VPD, which triggers tight stomatal regulation and conservative water use, both of which will become increasingly consequential under intensifying atmospheric water demand.

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1 | Introduction

Bioenergy is a critical climate change mitigation strategy towards advancing energy independence and greenhouse gas (GHG) emission reduction (Fuss et al. 2014). However, agriculture is already a major consumer of freshwater, and the expansion of biofuel crop production may further intensify this demand, with uncertain consequences for regional water availability (El-Araby 2024; Chukalla et al. 2025). The Southeastern United States (SE US) is projected to supply nearly one-third of national 36-billion-gallon biofuel target (USDA 2021), with sugarcane (*Saccharum officinarum*) emerging as a promising feedstock (Gomez-Casanovas et al. 2024; Blanc-Betes et al. 2025). Its role in a sustainable bioeconomy, however, depends on its ecohydrological performance, which remains poorly characterized in the context of land-use changes. A mechanistic understanding of evapotranspiration (ET) partitioning and drivers of water use efficiency (WUE) is therefore essential for predicting the hydrological consequences of sugarcane expansion in the SE US.

Meeting the national 36-billion-gallon biofuel target requires large-scale land-use conversion (Hudiburg et al. 2016). In the SE US, pasturelands account for roughly 34% of subtropical and tropical US agricultural land and represent a primary candidate for sugarcane expansion in the region (Dixon et al. 2014; Farmland Information Center 2022).

Evidence from other bioenergy crops suggests that the conversion from grasslands to bioenergy crops can strongly affect water fluxes and WUE (Eichelmann et al. 2016; Anapalli et al. 2019; Carvalho et al. 2024), though outcomes are highly context dependent. Yimam et al. (2017) found that replacing grasslands with switchgrass in the southern Great Plains increased annual ET by 2%–17%, reducing overall landscape-scale water availability, whereas Abraha et al. (2015) showed that converting Conservation Reserve Program grasslands to perennial switchgrass or mixed-prairie decreased ET, with precipitation driving the differences. While these findings are not directly transferable to sugarcane given its distinct canopy structure and water use characteristics, they underscore that the hydrological consequences of grassland-to-bioenergy conversion are unlikely to be uniform. Characterizing the specific hydrological impacts of pasture-to-sugarcane conversion therefore requires field-based ET measurements coupled with robust partitioning and WUE estimation frameworks.

Two interacting sources of uncertainty complicate the characterization of ET shifts following pasture-to-sugarcane conversion. First, how canopy structure, stomatal regulation, and rooting depth, and therefore ET and its components, change as sugarcane matures across ratoon cycles (i.e., regrowth following each harvest, without replanting) remains poorly constrained (Basnayake et al. 2015; Celis et al. 2023). Reductions in ET from plant to ratoon (regrowth following harvest) cane have been observed and attributed to less vigorous regrowth and a corresponding decline in transpiration (T) as the crop matures (Cabral et al. 2012; Singta et al. 2018). However, increased ET in first ratoon compared to plant cane (Santos et al. 2019) and no change across ratoon cycles (Bispo et al. 2022) have also been reported. Second, even where ET differences between land uses are observed, the underlying mechanisms cannot be resolved from ET alone. The higher biomass

and vegetation cover in sugarcane systems may promote greater T through enhanced canopy radiation interception and leaf-level water loss, whereas the sparser and shorter canopies, and greater soil moisture exposure of pasture systems tend to favor E over T (Hu et al. 2009; Dong et al. 2024). In addition, croplands often exhibit tighter stomatal regulation and greater sensitivity of g_s to VPD than grasslands, reflecting stronger coupling between C assimilation and water loss (Chen et al. 2023). In pastures, by contrast, a larger fraction of ET may arise from soil E (Basnayake et al. 2015; Eichelmann et al. 2016). While these contradictory findings likely reflect the context dependency of ET responses to climate, soil, and management, they also expose a key limitation of ET as a metric.

ET integrates both T and E and therefore it cannot resolve the distinct physiological and physical processes governing water use (Anderson et al. 2015; Alavi et al. 2024; Rotenberg et al. 2025). Partitioning ET into its constituent components is therefore critical to resolve how structural and physiological differences between land uses govern the conversion-driven shifts in water use, how these mechanisms evolve as the crop matures across ratoon cycles, and ultimately to evaluate the sustained hydrological and WUE consequences of pasture-to-sugarcane expansion.

Beyond canopy and stomatal effects, sugarcane has the potential to develop deep root systems capable of accessing subsurface moisture unavailable to shallow-rooted pasture grasses, sustaining T across a wider range of soil moisture conditions (Inman-Bamber et al. 2012). Together, these traits suggest that pasture-to-sugarcane conversion will shift ET partitioning toward greater T, although the extent to which these structural and physiological differences translate into higher ecosystem-level ET and WUE remains uncertain, as responses are modulated by VPD, soil moisture availability, and crop management (Inman-Bamber et al. 2012).

Here, we investigated how the conversion of pasture to sugarcane in subtropical Florida (FL) affects water fluxes and WUE over three growth cycles. Compared to pasture, we hypothesize that sugarcane will exhibit higher T and ET, driven primarily by structural traits such as a denser canopy and deeper root system that increase leaf area, total stomatal surface, and access to soil water. We expect these structural advantages to override the influence of stomatal sensitivity to VPD on canopy-scale water fluxes (Ellsworth and White Jr. 2024; Lunn et al. 2024; Takaragawa et al. 2025). We further predict that progressive increases in canopy development and rooting depth as the crop matures lead to an intensification of these effects across ratoon cycles. Finally, we hypothesize higher ecosystem-scale WUE in cane than in pasture, as croplands tend to have a tighter regulation of g_s , which strengthens the coupling between C assimilation and ET in cane. By identifying key ecological and physiological mechanisms influencing ET and WUE following conversion, this study provides actionable insights into the ecohydrological sustainability of sugarcane production.

2 | Methodology

2.1 | Site Description

The study was conducted from 2019 to 2022 at Archbold Biological Station's Buck Island Ranch (BIR), a 4290-ha commercial cow-calf ranch that operates as an ecological field

station (Lake Placid, Florida; 27°09'N, 81°11'W) and is a site in the USDA's Long-Term Agroecosystem Research (LTAR) network. The area has a typical, humid, subtropical climate with distinct seasons: a wet season (mid-May through mid-October) and a dry season (late-October through early-May). The area receives mean annual precipitation of 1300 mm, with ca. two-thirds of total annual precipitation falling from June to September (1980–2017). The area has a mean high summer air temperature of ca. 33°C (July–August) and mean minimum winter temperature of ca. 11°C (December–January) (1980–2017) (Thornton et al. 2016; DayMet database).

The experimental design consisted of three plots: one semi-native (SN; 16 ha), one improved (IMP; 16 ha) pasture and one IMP pasture that was converted to sugarcane (cane, hereafter; 34 ha) at the beginning of 2019. Details of experimental design, land use history and agronomic management were thoroughly described in Gomez-Casanovas et al. (2024). The IMP pasture and cane fields are adjacent to each other, and the SN pasture is less than 1 mile away from both sites. Therefore, all sites experienced the same subtropical climate, with minimal differences in precipitation, irradiance, and air temperature (data not shown). All sites are dominated by Immokalee sand, a soil series within the Spodosol order.

Briefly, both the SN and IMP pastures were established in 1950 and composed of C4 grasses. The SN pasture was dominated by native grasses such as purple bluestem (*Andropogon glomeratus* var. *glaucoptis*), redtop panicum (*Coleataenia longifolia*), carpetgrasses (*Axonopus* spp.), and creeping bluestem (*Schizachyrium stoloniferum*) (Boughton et al. 2022; Gomez-Casanovas et al. 2024) with patches of non-native bahiagrass (*Paspalum notatum*; Gomez-Casanovas et al. 2018), lacked drainage ditches and had never been fertilized. In contrast, the IMP pasture was dominated by Argentine bahiagrass (*Paspalum notatum* Flugge; Chamberlain et al. 2017). Both pasture types have historically been grazed by cattle (*Bos taurus* L.). Across the study period, SN pasture had a low to moderate grazing intensity, with a mean stocking rate of 0.17 animal unit (AU) ha⁻¹ (i.e., 0.17 cow-calf pairs ha⁻¹; 0.19 AU ha⁻¹ in 2019; 0.15 AU ha⁻¹ in 2020; 0.05 AU ha⁻¹ in 2021; and 0.3 AU ha⁻¹ in 2022), compared to IMP pasture, which had a heavy grazing intensity with a mean stocking rate of 0.67 AU ha⁻¹ (i.e., 0.67 cow-calf pairs ha⁻¹) (0.89 AU ha⁻¹ in 2019; 0.65 AU ha⁻¹ in 2020; 0.63 AU ha⁻¹ in 2021; and 0.52 AU ha⁻¹ in 2022). Historically, IMP pastures were extensively ditched, fertilized with nitrogen (ca. 26 kg ha⁻¹ every 2 years) and limed (ca. 229 kg ha⁻¹ every 5 years; Swain et al. 2013). Previous to 1986, these pastures were also fertilized with phosphorus. These amendments were discontinued for the duration of this study. Both pastures were managed under traditional regional practices including prescribed fire (Boughton et al. 2022). Soils under both pasture types are dominated by Immokalee sand, a soil series within the Spodosol order.

The cane plot was established in 2019 on previously managed IMP pasture. Prior to conversion, the site was grazed by cattle at an average intensity of 1.1 AU ha⁻¹ year⁻¹ and regularly fertilized (nitrogen, ca. 26 kg ha⁻¹ every 2 years) and limed (ca. 229 kg ha⁻¹ every 5 years; Swain et al. 2013). Previous to 1986, the pasture was also fertilized with phosphorus. Before cane establishment, bahiagrass was terminated with herbicide and the

field was tilled immediately afterward. During our study, cane was fertilized with solid N-P-K fertilizer and managed with herbicide applications for weed control (Table S1). The cane field was seepage-irrigated through drainage ditches. Prior to harvest, standard regional practices were followed to burn leaves and tops of the stalks, and biomass was harvested by cutting stalks approximately 10 cm above the soil surface. Soils beneath the sugarcane are dominated by Immokalee sand, a soil series within the Spodosol order, and have a similar bulk density and organic matter to IMP pastures before land conversion.

In our study, we followed standard definitions in cane literature and defined plant cane (PC) as cane crop from planting until first harvest (here, from 2/6/2019 to 2/16/2020), first ratoon cane (FRC) as cane crop from first to second harvest (here, from 2/17/2020 to 2/8/2021), and second ratoon cane (SRC) as cane crop from second to third harvest (here, from 2/9/2021 to 4/6/2022).

2.2 | Eddy Covariance Data Analysis

Eddy covariance towers were established at the center of each plot to measure fluxes from February 2019 to April 2022. Flux measurements, tower equipment, auxiliary instrumentation were thoroughly described in Gomez-Casanovas et al. (2024). Briefly, half-hourly raw flux data were collected at 10 Hz. This high-frequency data was processed with EddyPro 7.0.9 (LI-COR Biosciences, US) following Gomez-Casanovas et al. (2020). A double-rotation scheme was used to align the coordinate system to the main wind direction, and crosswind correction of sonic temperature was implemented by the firmware (R. M. Young Company Inc., USA). Lagged covariances between vertical wind velocity and each flux scalar were computed and applied to account for lag times between the sonic anemometer and the flux sensors. Humidity and spectral corrections for high-pass and low-pass filtering were implemented. Spikes in raw flux data were eliminated, and the quality of each half-hour average was determined following the 1–9 method (Foken et al. 2004) and low-quality data such as nighttime periods with no turbulent mixing were eliminated (flags > 7). A Hsieh cross-wind-integrated flux footprint model was used to identify periods when the fluxes corresponded to areas outside the plot's edges (Hsieh et al. 2000).

Visualization and QA/QC of data were performed using PyFluxPro 3.4.23 (Isaac et al. 2017). Missing half-hour soil-meteorological parameters and latent heat (LE) data were gap filled using the eddy covariance and flux gap filling online tool (Reichstein et al. 2005). Fluxes were filtered for low friction velocity (u^*) and gap-filled using the marginal distribution sampling approach. Physically plausible thresholds based on visual inspection of half-hour data series as well as standard QA/QC of half-hourly flux data were applied to remove spurious observations (Zeri et al. 2013; D. Baldocchi 2014; Isaac et al. 2017; Gomez-Casanovas et al. 2020). Briefly, LE were discarded if they were < -100 or > 700 W m⁻²; sensible heat flux (H) was discarded if it was < -150 or > 400 W m⁻². Meteorological variables including vapor pressure deficit (VPD), relative humidity (RH), air temperature (T_{air}), air pressure (p_s), soil temperature (T_{soil}) were discarded if they were not within 0–50 hPa, 0%–110%,

−10°C to 60°C, 80–110 kPa, and −10°C to 60°C, respectively (Nicholls et al. 2024).

Total uncertainty in fluxes was estimated by error propagation accounting for both random measurement error and gap-filling uncertainty (Richardson and Hollinger 2007). Because eddy covariance measurements are difficult to replicate spatially and integrate continuous fluxes over large heterogeneous source areas, this study was consistent with most eddy covariance-based studies that used uncertainty propagation rather than site replication for statistical inference. Uncertainty estimates in water fluxes have been previously used to test differences between land uses and ratoon age (Aubinet et al. 2012; D. D. Baldocchi 2020; Xu et al. 2022; Gomez-Casanovas et al. 2024). In this study, overlapping uncertainty bounds between two land uses were interpreted as indicating similar flux magnitudes, while non-overlapping uncertainty bounds were interpreted as indicating meaningful differences between them.

Ecosystem total water use (evapotranspiration; ET) was calculated from the eddy covariance-derived LE following the energy balance approach:

$$ET = \frac{LE}{\gamma \times \rho_w} \quad (1)$$

where γ = latent heat of vaporization, ρ_w = water density.

2.3 | Evapotranspiration Partitioning

The Transpiration Estimation Algorithm (TEA) was used to partition ecosystem ET into T and E using the eddy covariance data and auxiliary measurements (Nelson et al. 2018; Nelson et al. 2020). The TEA exploits the coupling between C uptake (i.e., gross primary productivity; GPP) and plant water use to train a random forest (RF) model to predict T (i.e., $T = GPP/WUE$) and E as the residual (i.e., $E = ET - T$) at each timestamp (i.e., every half-hour interval).

Briefly, the algorithm first identified periods when T is expected to dominate ET (i.e., $T/ET \approx 1$) using multiple data filters including periods when half-hourly GPP $> 0.05 \mu\text{mol C m}^{-2} 30 \text{ min}^{-1}$; daily GPP $> 0.5 \text{ g C m}^{-2} \text{ day}^{-1}$, air temperature (T_{air}) $> 5^\circ\text{C}$; incoming radiation (R_g) $> 0 \text{ W m}^{-2}$; and a conservative surface wetness index (CSWI) < -0.5 (Nelson et al. 2018).

The CSWI was conceptualized as a shallow bucket model, simulating surface water balance relative to the most recent precipitation event and reflecting how close surface soil moisture is to field capacity (higher surface wetness is assumed to have higher E) (Nelson et al. 2018):

$$S_t = S_{t-1} + P_t - ET_t \quad (2)$$

where P_t = precipitation at time t , S_t , S_{t-1} = surface water storage for each half-hourly time-stamp t and $t-1$, and ET_t = ET at time t .

The CSWI was then calculated as follows:

$$\text{CSWI} = \max(S_t, \min(P_t, S_{\text{max}})) \quad (3)$$

where S_{max} defined as maximum allowable surface water storage, was set to 5 mm based on model calibration conducted by Nelson et al. (2018).

Periods with CSWI ≥ -0.5 mm were excluded from model training, as higher values indicate wetter surface conditions associated with elevated E contribution to total ET. Following the data filtering, a quantile RF Regressor machine learning approach (Meinshausen and Ridgeway 2006) was trained to learn the relationship between the environmental factors controlling the plant-driven ecosystem WUE at a half-hour time scale ($\text{hh-eWUE} = GPP/ET$). During filtered periods (CSWI < -0.5), the model assumes that E was negligible relative to T ($T/ET \approx 1$), such that $ET \approx T$ and hh-eWUE approximated plant-driven WUE rather than a mixed soil–plant signal. The RF model was trained using a set of input features including both meteorological variables, T_{air} , relative humidity (RH), VPD, wind speed (u), potential radiation (R_{g_pot}), and ground heat flux (G), as well as GPP. By analyzing these inputs, the RF identified patterns that explained variations in plant-driven hh-eWUE following Nelson et al. (2018).

The quantile RF ensemble approach uses multiple decision trees ($n = 100$) to be able to capture the complex, nonlinear relationships between the controlling factors and plant-driven hh-eWUE . In our study, each tree trained on a random bootstrap sample of this filtered data and used a random subset of features at each split, allowing the model to robustly predict plant-driven hh-eWUE across the full half-hourly timeseries (Nelson et al. 2018; Nelson et al. 2020). This allowed the model to “learn” how varying environmental conditions influenced plant-driven hh-eWUE . Once trained, the RF was then able to predict hh-eWUE for all half hourly data using the behavior learned from the periods when plants were driving WUE. This predicted hh-eWUE was then used to estimate plant-driven T across the entire dataset as follows:

$$T = GPP / \text{hh-eWUE}_{\text{predicted}} \quad (4)$$

Rather than producing a single mean prediction, the quantile RF estimates the conditional distribution of plant-driven hh-eWUE for each half-hourly observation. In this equation, final partitioned fluxes were extracted from the 75th percentile of the RF predicted hh-eWUE distribution, following the sensitivity analyses reported by Nelson et al. (2018) and Nelson et al. (2020). The 75th percentile was selected to reduce the influence of incidental background evaporation on the estimated plant-driven relationship. Although the model assumes that E is negligible when CSWI < -0.5 , some residual soil or surface E may still occur during these periods. Using the upper percentile of the predicted hh-eWUE distribution therefore assigns greater weight on conditions which mostly represent T-dominated water loss and limits the extent to which residual background E inflates the estimated T flux (Table S3). With nighttime T set to zero, E for each half hour was estimated as follows:

$$E_{\text{TEA}} = ET - T_{\text{TEA}} \quad (5)$$

All data processing and partitioning steps followed the publicly available reference source code described in Nelson et al. (2020). The Model hyperparameters were selected based on the sensitivity analysis done in Knauer et al. (2018).

2.4 | Stomatal and Aerodynamic Conductance

Stomatal conductance (g_s) was estimated at canopy scale with the inverted Penman-Monteith equation using the aerodynamic conductance (g_a) and surface conductance within the R package “bigleaf” model framework (Monteith 1965) using the function *surface.conductance* following Knauer et al. (2018) and Knauer et al. (2022):

$$g_s = \frac{\gamma LE_T g_a}{\Delta (R_n - G) + \rho C_p VPD g_a - LE_T (\Delta + \gamma)} \quad (6)$$

where Δ (Pa K⁻¹) was the slope of saturated vapor pressure, ($R_n - G$, W m⁻²) was available energy (difference between net radiation and ground heat flux), ρ (kg m⁻³) was air density, C_p (J kg⁻¹ K⁻¹) was air heat capacity, γ (Pa K⁻¹) was psychrometric constant, VPD (Pa) was vapor pressure deficit, LE_T (W m⁻²) was latent heat flux derived from transpiration, and g_a (ms⁻¹) was aerodynamic conductance.

We used the Monteith–Unsworth model to estimate g_a (Monteith and Unsworth 1990, 2013) within the R package “bigleaf” model framework using the function *aerodynamic.conductance* following Knauer et al. (2018) and Knauer et al. (2022):

$$g_a^{[-1]} = \left(\frac{u}{u^{*2}} + 6.2u^{*-2/3} \right) \quad (7)$$

where u (ms⁻¹) was wind speed at reference height, u^* was friction velocity (ms⁻¹).

Uncertainty in both g_s and g_a was expressed as the standard error, calculated as the standard deviation divided by the square root of the sample size.

At the ecosystem scale, surface conductance includes both stomatal and soil conductance. Physiologically significant interpretations of g_s can be unreliable because the relationship between surface conductance and atmospheric variables, often attributed to stomatal regulation, may in fact be driven by soil conductance and soil–atmosphere coupling, even in the absence of plants (Vargas Zeppetello et al. 2023). This can lead to misattributing variability to stomatal behavior and ignoring the influence of atmospheric conditions on soil conductance. To ensure that g_s is physiologically meaningful, we restricted the analysis to periods when g_s closely represented canopy conductance (g_c). This condition is met when vegetation is photosynthetically active and neither soil nor canopy surfaces are wet, thereby minimizing contributions from non-stomatal E.

For this purpose, LE was derived specifically from T partitioned by the TEA framework, excluding soil E as this framework focused only on plant-controlled fluxes, avoiding soil contributions (Kelliher et al. 1995; Nelson et al. 2020). Calculations were further limited to daytime conditions ($F_{\text{pard}} > 10 \mu\text{mol m}^{-2} \text{s}^{-1}$), when vegetation was photosynthetically active, ensuring stomatal-driven T (Baldocchi et al. 2001; Novick et al. 2016). Additional filtering accounted for periods with low g_a that were excluded to remove conditions of inadequate atmospheric mixing (Baldocchi and Meyers 1998; Baldocchi et al. 2002; Knauer et al. 2018), and timestamps with zero VPD were also excluded

(Oren et al. 1999; Medlyn et al. 2011) to retain periods when T was actively driven by VPD.

2.5 | Stomatal Behavior Models

The Unified Stomatal Optimization model (USO; Medlyn et al. 2011) and the Oren model (Oren et al. 1999) characterize stomatal behavior to VPD from complementary perspectives. The USO model provides a mechanistic, optimization-based representation of how stomata balance C gain against water loss. This model yields the parameter g_1 as a water-use strategy indicator. The Oren model quantifies the empirical sensitivity of g_s to VPD through a log-linear relationship, independently of assumptions about C assimilation. Together, these formulations allow stomatal regulation to be interpreted both in terms of underlying plant water-use economics and in terms of the magnitude and direction of stomatal response to VPD across land-use types.

2.5.1 | USO Model

The USO model (Medlyn et al. 2011) provides a mechanistic representation of g_s as a function of VPD and atmospheric CO₂ concentration. It relies on the theory that plants optimize stomatal regulation to balance C gain and water loss, maintaining the trade-off between photosynthesis and T and enhancing WUE under varying VPD (Cowan and Farquhar 1977). The USO model has been implemented extensively in multiple land surface models (De Kauwe et al. 2015; Haverd et al. 2018; Lawrence et al. 2019; Sabot et al. 2022), supporting its use for physiologically meaningful interpretation of stomatal regulation in this study via the bigleaf R Package (function: *stomatal.slope*) (Knauer et al. 2018; Knauer et al. 2022).

The USO model integrates the Ball-Berry model of g_s (Collatz et al. 1991), the Farquhar photosynthesis model (Farquhar et al. 1980; Arneth et al. 2002), and the optimal stomatal control theory of Cowan–Farquhar stomatal optimization theory (Cowan and Farquhar 1977). Using the USO model, stomatal responses were characterized by the parameter g_1 , which describes how stomata respond to VPD and net C assimilation as follows:

$$g_s = g_0 + 1.6 \left(1 + \frac{g_1}{\sqrt{D_s}} \right) \frac{A_n}{C_s} \quad (8)$$

where D_s is vapor pressure deficit (kPa); A_n is net photosynthesis ($\mu\text{mol CO}_2 \text{ m}^{-2} \text{s}^{-1}$), represented as GPP in the present study; C_s is atmospheric CO₂ concentration ($\mu\text{mol mol}^{-1}$); g_s is stomatal conductance to water vapor ($\text{mol m}^{-2} \text{s}^{-1}$); g_0 is the residual conductance to water vapor when A_n approaches zero ($\text{mol m}^{-2} \text{s}^{-1}$), and it was fitted with g_1 as residual or baseline conductance to water vapor when net photosynthesis approached zero; and g_1 (kPa^{0.5}) is the slope parameter indicating stomatal responsiveness and quantifying how sensitive g_s is with changes in VPD, 1.6 is a factor converting from conductance to CO₂ to conductance to water vapor.

The parameter g_1 reflects the optimal stomatal behavior through minimizing the integrated sum of $(T - \lambda A_n)$ over time (δ_t). Here,

λ is a Lagrange multiplier in the optimization framework (Katul et al. 2010; Han et al. 2023) that represents the marginal water cost of C gain (Cowan and Farquhar 1977; Medlyn et al. 2011) and thus reflects stomatal water-use strategy.

Lower g_1 indicates higher λ , prioritizing water conservation and suggesting more conservative stomatal behavior, whereas higher g_1 corresponds to lower λ , prioritizing C assimilation and suggesting less conservative stomatal strategy, particularly under increasing VPD (Lin et al. 2015).

2.5.2 | Oren Model

Stomata typically respond to increasing VPD by partially closing, thereby moderating T losses (Lange et al. 1971). Previous studies have shown that this response results in a non-linear increase in T, which reaches a plateau and may even decline under very high VPD (Jarvis 1980; Monteith 1995; Grossiord et al. 2020). Evidence further suggests that stomatal closure is triggered primarily by T rather than VPD itself, indicating a feedback mechanism linked to water loss from leaves (Mott and Parkhurst 1991).

To quantify this stomatal response to VPD, we applied the Oren model (Oren et al. 1999), implemented via the *bigleaf* R package (function: *stomatal.sensitivity*) (Knauer et al. 2018; Knauer et al. 2022). The Oren model describes a log-linear relationship between g_s and VPD, providing a quantitative measure of how stomata respond to VPD as follows:

$$g_s = b - m \ln(\text{VPD}) \quad (9)$$

where g_s is stomatal conductance ($\text{mol m}^{-2} \text{s}^{-1}$), VPD is vapor pressure deficit (kPa), $-m$ was the slope (i.e., $-m = -\frac{\delta g_s}{\delta \ln D}$) and quantifies the sensitivity of g_s to VPD and b was intercept with respect to $\ln(\text{VPD})$ and corresponds to reference stomatal conductance ($g_{s\text{REF}}$) at $\text{VPD} = 1$ kPa.

The Oren model provides not only a quantitative measure of stomatal sensitivity to VPD, defined as stomatal closure or openness, but also a framework for interpreting plant water-use strategies along the continuum from drought avoidance to tolerance (Oren et al. 1999).

In our study, the ratio $(-m/b)$ was used as an indicator of normalized stomatal sensitivity to VPD, and hence it provides a relative measure of stomatal response to VPD. A higher $|-m/b|$ ratio indicates rapid stomatal closure and a more conservative water-use strategy, whereas a lower $|-m/b|$ ratio reflects lower stomatal sensitivity, with stomata remaining open longer as VPD increases (Oren et al. 1999).

2.6 | Estimation of WUE Metrics

WUE can be quantified as a scale-dependent metric that integrates different aspects of the C and water relationship across different levels of biological systems. In this study, we estimated four WUE metrics spanning canopy, plant, ecosystem, and biome scale to characterize how effectively water resources are converted into C assimilation and biomass across the study sites. Together, these metrics link stomatal regulation to GPP, GPP to

total ET, water consumption to harvestable productivity, and net ecosystem C balance (NECB) to total ET, providing a multi-scale picture of agroecosystem water budget. Total uncertainty in WUE metrics was estimated by error propagation of the numerator and the denominator.

At the canopy scale, intrinsic WUE (iWUE) was estimated as follows (Hoover et al. 2023; Zhang et al. 2019):

$$\text{iWUE} = \frac{\text{GPP}}{G_s} \quad (10)$$

where GPP represents gross C assimilation; g_s represents canopy-scale stomatal conductance.

At the plant scale, harvested WUE (hWUE) was estimated as follows (Zeri et al. 2013):

$$\text{hWUE} = \frac{\text{Harvested biomass}}{\text{ET}} \quad (11)$$

where harvested biomass represents mechanically harvested yield for cane and grazed or consumed biomass for pasture, the latter obtained using the movable cage method; data are reported in Gomez-Casanovas et al. 2024; ET is evapotranspiration.

At the ecosystem scale, ecosystem WUE (eWUE) was estimated as follows (Wagle, Kakani, and Huhnke 2016; Wagle, Xiao, et al. 2016; Hoover et al. 2023):

$$\text{eWUE} = \frac{\text{GPP}}{\text{ET}} \quad (12)$$

where GPP, gross primary productivity; ET, evapotranspiration.

At the biome scale, biome WUE (bWUE) was estimated as follows:

$$\text{bWUE} = \frac{\text{NECB}}{\text{ET}} \quad (13)$$

where ET is evapotranspiration; and NECB, net ecosystem C balance which represents the net exchange of C between the ecosystem and the atmosphere, and integrates the net ecosystem CO_2 exchange as well as all C inputs (i.e., biomass from prior land use, cattle dung input) and outputs (harvest biomass, fire). The NECB indicates whether the system acts as a net C source (positive NECB) or a sink (negative NECB) (Gomez-Casanovas et al. 2024). Because bWUE is defined as the ratio of NECB to ET, it inherits the sign convention of NECB. Accordingly, interpretation of bWUE therefore requires considering both its magnitude and sign rather than treating it as a conventional WUE metric, where a higher negative NECB reflects greater bWUE. Specifically, positive bWUE reflects net C source per unit water use, whereas negative bWUE indicates net C sink per unit water use.

2.7 | Statistical Analysis

To improve model interpretability and reduce the collinearity among environmental parameters influencing T and ET, we calculated a variance inflation factor (VIF) using the

variance_inflation_factor function from *statsmodels.stats* library (version 0.14.6) in Python (version 3.12.3). Predictors with $VIF > 10$ were considered highly collinear and were excluded stepwise, prioritizing retention of ecologically interpretable variables influencing T and ET (Hou et al. 2020; Dertli et al. 2024). Based on these diagnostics and ecological relevance, a common set of environmental parameters (i.e., VPD, soil water content; SWC, photosynthetic active radiation; PAR, ambient CO_2 concentration, u^*) was selected for inclusion at all sites. We then fitted forward stepwise linear regression using *LinearRegression* function from *sklearn.linear_model* library (version 1.7.0) in Python (version 3.12.3). Starting with an intercept-only model (i.e., $y = \beta_0$; where y is the dependent variable and β_0 is the intercept), drivers were added one at a time; followed by refitting the model and computing Akaike Information Criterion (AIC). The combinations of parameters yielding reduction in AIC were retained and this process was repeated until no additional predictor lowered AIC, thereby balancing improved fit against increased model complexity. The calculation of AIC was as follows:

$$AIC = n \ln\left(\frac{RSS}{n}\right) + 2k \quad (14)$$

where n = sample size, k = number of independent parameters of the model, RSS = sum of squared residual.

For the final selected model at each site, we evaluated model performance using coefficient of determination (R^2), root mean squared error (RMSE). Lastly, we calculated standardized regression coefficients to calculate relative importance (%) for each driver as follows:

$$\text{Relative Importance (\%)} = \frac{|\beta_j^{\text{std}}|}{\sum |\beta_j^{\text{std}}|} \times 100 \quad (15)$$

where $|\beta_j^{\text{std}}|$ the standardized regression coefficient for predictor j .

To characterize the g_s -VPD relationship, the half-hourly g_s values were binned by VPD (bin width = 0.2 kPa) and 95% confidence intervals (CI) within each bin for each land use and study period were calculated following methods described in Novick et al. (2016) (Figure S4).

To estimate uncertainty in seasonal sums from the modelled T and E, we used a block-bootstrap approach that considers both the time-series structure and model variance. Each site and growing season were divided into fixed length blocks to preserve temporal dependence. These blocks were repeatedly resampled ($n = 1000$), and small random noise based on the model's standard error was added to each time step. For each resampled series, values were summed to produce a possible seasonal sum. For each bootstrap iteration, resampled block values were summed to produce a seasonal total; the spread of these totals across all iterations was then used to quantify uncertainty for each site and growing season. These uncertainties represent the 95% CI from the block bootstrap Montecarlo simulations. This bootstrapped uncertainty was also performed from the SciPy library (version 1.16.1) in Python (version 3.12.3) (Wang et al. 2015; Jian et al. 2022).

Standard errors for the fitted stomatal model parameters m , b , and g_1 were estimated based on the variance covariance matrix of the fitted model using the *bigleaf* R package (R version: 4.4.2. *bigleaf* version 0.8.2). The standard error was calculated as the square root of the diagonal elements (i.e., variance of the mean of the specific estimated variable) of the covariance matrix. For the $| -m/b |$ parameter the standard error was estimated by error propagation based on uncertainty from both m and b parameters.

For USO, AIC and RMSE were used to assess the model fit. Specifically, AIC accounted for model complexity while quantifying goodness of fit, whereas RMSE provided a direct measure of predictive error, making both metrics more informative for assessing nonlinear, multi parameter formulations. On the other hand, R^2 was used to quantify the proportion of variance in g_s explained by modeled stomatal response to VPD. All these analyses were conducted in R (version 4.4.2) using the *bigleaf* package (version 0.8.2).

3 | Results

3.1 | Meteorological Conditions

RH, PAR, and T_{air} were similar across study years, whereas precipitation and VPD varied among years (Figure 1 and Figure S1). Total precipitation increased over time, from 1158 mm (January 2019–February 2020) to 1234 mm (March 2020–February 2021) and 1509 mm (March 2021–April 2022) (Figure S1). In contrast, VPD ranged from 680 to 717 Pa across years, declining from 691 to 680 Pa before increasing to 717 Pa (Figure 1).

3.2 | Evapotranspiration and Its Partitioning

Overall, ET was slightly lower in cane than improved pasture (IMP) by 1.7%, and consistently higher than in semi-native pasture (SN) by 21% (Figure 2). Although these ET differences between cane and IMP were small, differences varied markedly across growth cycles. Immediately after conversion, ET in plant cane (2/6/2019 to 2/16/2020; PC) was 13% lower than in IMP. With increasing stand age, ET in first and second ratoon cane exceeded that of IMP (FRC, 2/17/2020 to 2/8/2021; and SRC, 2/9/2021 to 4/6/2022, respectively) by 6% and 4%, respectively.

Across land uses, T followed a similar pattern, averaging 8% lower in cane than in IMP and 19% higher than in SN on average across growth cycles (Table 1, Figure S2). Annual T ranged from 397 to 603 mm $H_2O \text{ m}^{-2} \text{ year}^{-1}$ in cane, from 435 to 616 in IMP, and from 373 to 491 in SN. Across all land uses, T was the dominant component of ET (Figure S2), contributing up to 72%–77% of total water use (Table 1).

Compared to ET and T, E showed contrasting patterns across land uses. On average, E was higher in cane than in both IMP (19%) and SN (26%), and differences varied across growth cycles (Table 1 and Figure S2). Shortly after conversion, E in PC was lower than in both IMP (14%) and SN (3%). As the cane stand matured, however, E increased substantially. In FRC, cane E exceeded IMP by 49% and SN by 70%, while in

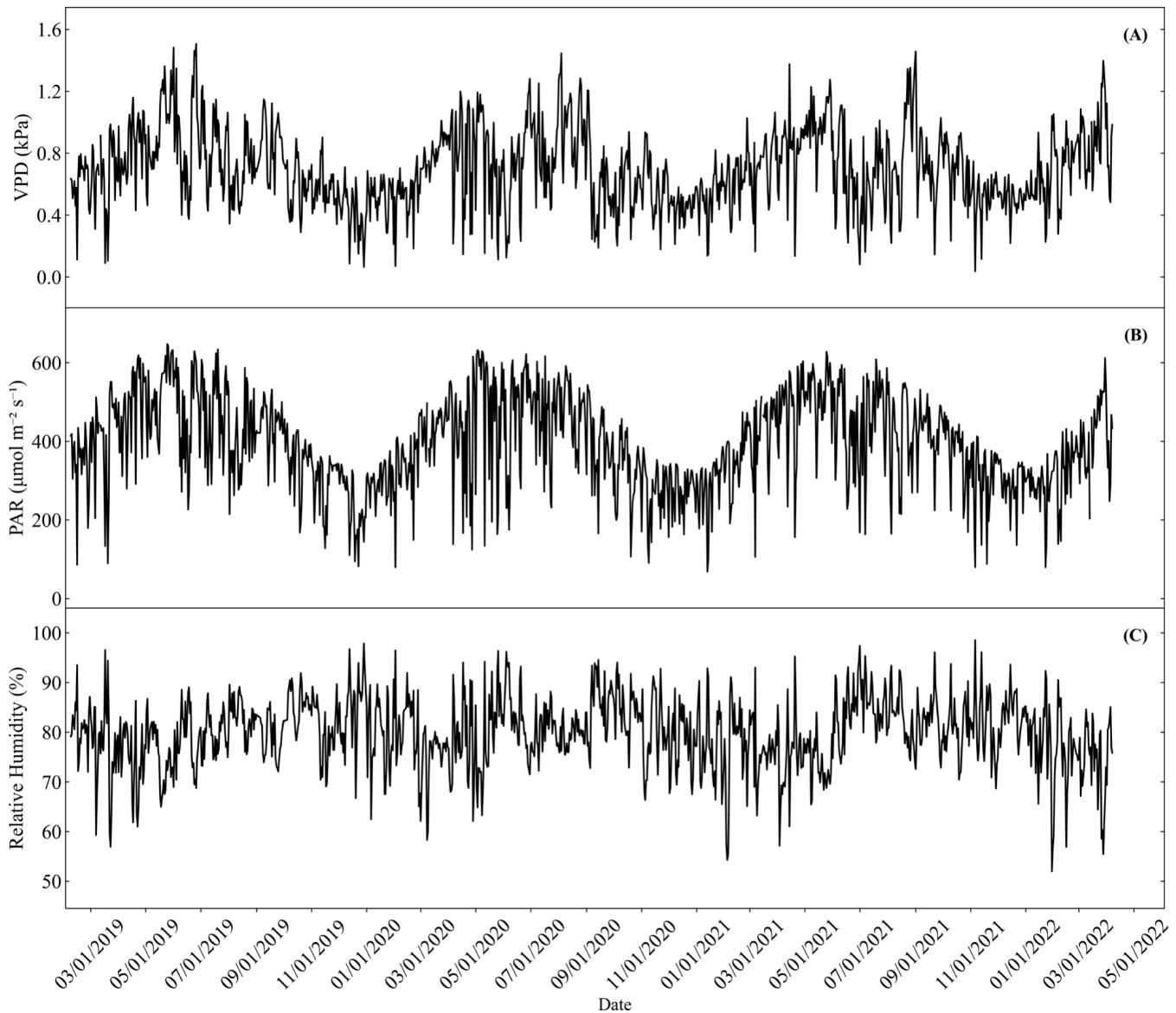


FIGURE 1 | Seasonal variation in (A) vapor pressure deficit (VPD) and (B) photosynthetically active radiation (PAR), and (C) relative humidity (RH) in 2019, 2020, 2021, and 2022.

SRC it exceeded the reference ecosystems by 27% and 20%, respectively.

Variations in ET and T were explained by a combination of environmental drivers, with VPD and PAR as the dominating factors across all land uses and minimal contributions from ambient CO₂ concentration, friction velocity (u^*), and soil water content (SWC) (Table 2). While both VPD and PAR explained most variation in ET and T in cane and IMP, PAR was the primary driver in SN.

3.3 | Stomatal Conductance and Sensitivity

Over the course of the study, g_s in cane was consistently lower than in IMP but higher than in SN (Figure 3A), while g_a in cane was consistently higher than in both pastures (Figure S3). Following conversion, g_s in PC was 35% lower than in IMP but 47% higher than in SN, mirroring the land use differences

observed for ET and T (Figure 3B). Differences in g_s between cane and IMP decreased with ratoon age.

Overall g_1 , which reflects stomatal behavior in balancing C gain and T, was 31% lower in cane than in IMP and 22% lower than in SN (Figure 4). These differences varied systematically across growth cycles (Figure 4A). Following conversion, g_1 in PC was 74% and 64% lower than in IMP and SN, respectively; in FRC differences narrowed to 30% and 35%, whereas in SRC g_1 exceeded both IMP and SN by 9% and 25%, respectively (Figure 4B).

Overall, the $| -m/b |$ ratio, which reflects stomatal sensitivity to VPD relative to reference conductance, was higher in cane than in both pastures (Figure 5). Differences between land uses varied across growth cycles (Figure 5). On average, the ratio was 59% higher in cane than in IMP and approximately 8-fold that of SN (Figure 5A). Following conversion from IMP, the $| -m/b |$ ratio in PC was 56% higher than in IMP while FRC showed

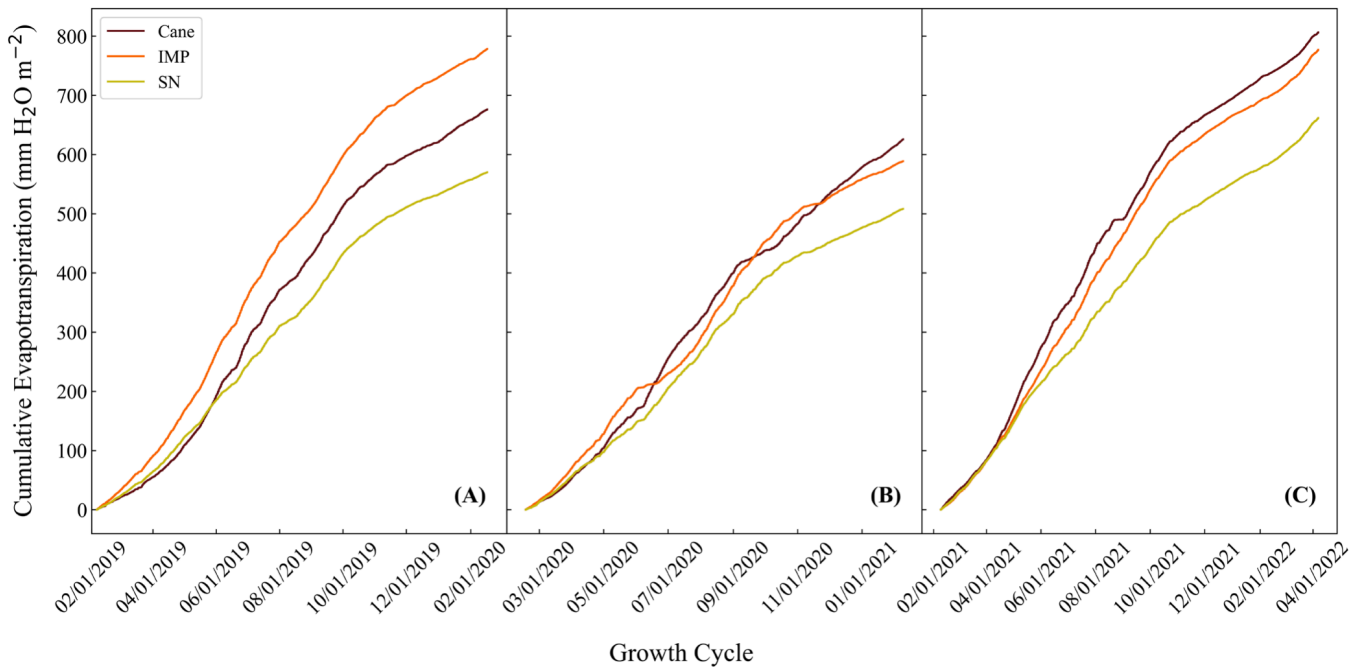


FIGURE 2 | Cumulative evapotranspiration (ET) for sugarcane (cane), improved pasture (IMP), and semi-native pasture (SN) in 2019, 2020, 2021, and 2022. Plant cane (PC) was defined as sugarcane crop from planting until first harvest (here, from 2/6/2019 to 2/16/2020), first ratoon cane (FRC) as cane crop from first to second harvest (here, from 2/17/2020 to 2/8/2021), and second ratoon cane (SRC) as cane crop from second to third harvest (here, from 2/9/2021 to 4/6/2022).

TABLE 1 | Evapotranspiration (ET) partitioning across the study periods.

Time period	Land use	Cumulative E (mm H ₂ O m ⁻² year ⁻¹)	Cumulative T (mm H ₂ O m ⁻² year ⁻¹)
2/6/2019 to 2/16/2020	PC	152.10 ± 2.16	524.03 ± 7.44
	IMP	176.45 ± 2.39	601.99 ± 8.16
	SN	157.21 ± 2.19	412.76 ± 5.75
2/17/2020 to 2/8/2021	FRC	228.55 ± 3.13	397.11 ± 5.43
	IMP	153.08 ± 2.28	435.61 ± 6.48
	SN	134.22 ± 1.95	373.95 ± 5.45
2/9/2021 to 4/6/2022	SRC	202.90 ± 2.61	603.29 ± 7.76
	IMP	160.13 ± 2.10	616.61 ± 8.09
	SN	169.59 ± 2.23	491.92 ± 6.47
Entire study 2/6/2019 to 4/6/2022	Cane	194.52 ± 2.66	508.14 ± 6.95
	IMP	163.22 ± 2.26	551.41 ± 7.61
	SN	153.67 ± 2.13	426.21 ± 5.91

Note: Evapotranspiration (ET) partitioning into evaporation (E; non-productive water loss: mm H₂O m⁻² year⁻¹) and transpiration (T; productive water use: mm H₂O m⁻² year⁻¹) for sugarcane (cane), improved pasture (IMP), and semi-native pasture (SN) across the study period and by year in 2019, 2020, 2021, and 2022. PC was defined as sugarcane crop from planting until first harvest (here, from 2/6/2019 to 2/16/2020), FRC as cane crop from first to second harvest (here, from 2/17/2020 to 2/8/2021), and SRC as cane crop from second to third harvest (here, from 2/9/2021 to 4/6/2022). Overlapping uncertainty bounds between two land uses were interpreted as indicating similar flux magnitudes, while non-overlapping uncertainty bounds were interpreted as indicating meaningful differences between them.

TABLE 2 | Model performance for identifying drivers of evapotranspiration.

Land use	AIC	RMSE	R ²
Model fit for drivers of T variability			
Cane	-300,973.2	0.034	0.66
IMP	-311,751.4	0.028	0.77
SN	-395,998.8	0.022	0.73
Model fit for drivers of ET variability			
Cane	-291,863.2	0.037	0.71
IMP	-306,060.8	0.03	0.80
SN	-386,927.5	0.024	0.79

Note: Performance of the forward stepwise regression model in identifying the key drivers of variation in evapotranspiration (ET) and transpiration (T). Model performance was evaluated using the Akaike information criterion (AIC), root mean square error (RMSE), and coefficient of determination (R²).

similar values to IMP. In SRC, the ratio increased again, exceeding IMP and SN by 158% and 340%, respectively (Figure 5B).

The USO model provided the best fit across land uses, as indicated by the lowest AIC (more negative values) and RMSE (Table S2). The Oren model showed a weaker fit than the USO model, with relatively low R² (Table S2); nevertheless, the stomatal sensitivity parameters (i.e., $-m$ and $| -m/b |$ ratio) were well-constrained with small standard errors (Figure 5; Table S2). Despite these relatively low R², statistically meaningful differences in stomatal sensitivity parameters were observed across land uses and study periods.

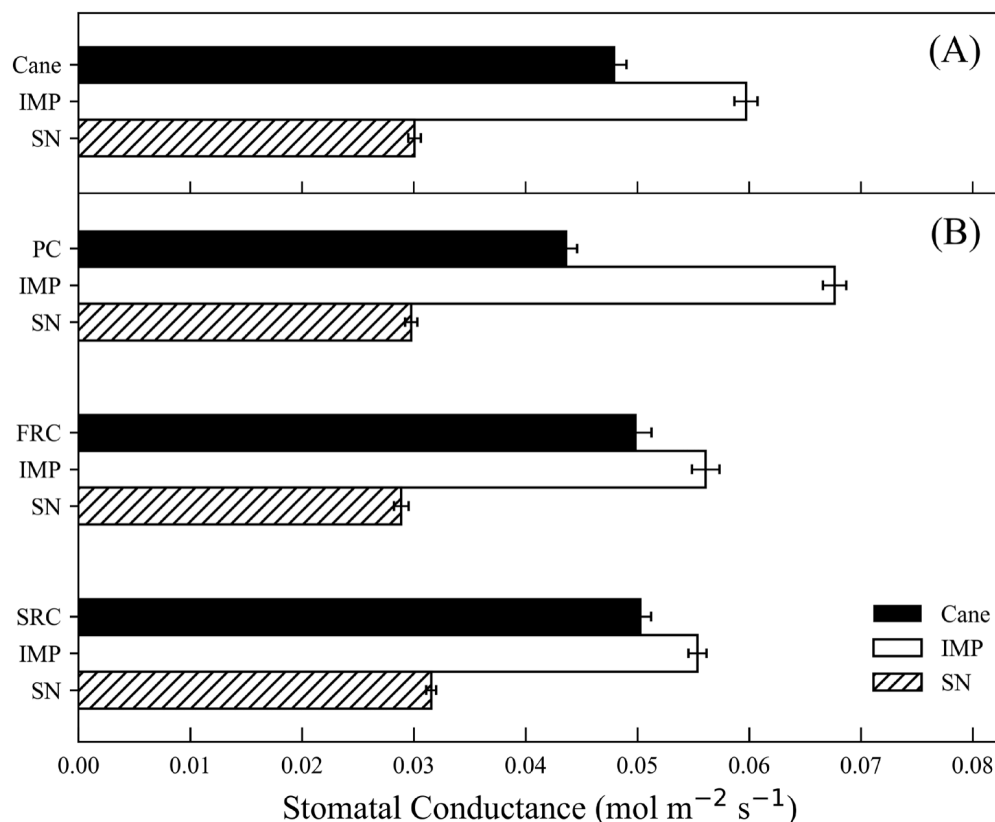


FIGURE 3 | Mean stomatal conductance (g_s) for sugarcane (cane), improved pasture (IMP), and semi-native pasture (SN) across the study period (A) and by year in 2019, 2020, 2021, and 2022 (B). PC was defined as sugarcane crop from planting until first harvest (here, from 2/6/2019 to 2/16/2020), FRC as cane crop from first to second harvest (here, from 2/17/2020 to 2/8/2021), and SRC as cane crop from second to third harvest (here, from 2/9/2021 to 4/6/2022). Overlapping uncertainty bounds between two land uses were interpreted as indicating similar g_s magnitudes, while non-overlapping uncertainty bounds were interpreted as indicating meaningful differences between them.

3.4 | WUE Metrics

Overall, $iWUE$ (GPP/g_s) was higher in cane than in both IMP (50%) and SN (16%), indicating greater stomatal C assimilation efficiency per unit water loss (Figure 6). Relative to IMP, $iWUE$ was consistently higher in cane across all growth cycles, with the largest difference in PC (88%) and more moderate differences in FRC (34%) and SRC (33%) (Figure 6). Relative to SN, $iWUE$ was similar in FRC but higher in PC and SRC by 30% and 19%, respectively.

At the plant and ecosystem scales, $hWUE$ (harvest/ET) and ecosystem WUE (GPP/ET) reflect how efficiently crops convert water into yield and gross productivity, respectively. In cane, $hWUE$ was 3–9 fold higher and $eWUE$ 22%–51% higher than in pastures (Figures 7 and 8), though differences varied across years. For $hWUE$, cane exceeded both pastures across all growth cycles, with the largest differences in PC (5–21 fold), followed by FRC (3–8 fold) and SRC (2–5 fold) relative to IMP and SN (Figures 7 and 8). Similarly, $eWUE$ was higher in cane across all growth cycles, with PC showing the greatest differences relative to IMP (39%) and SN (61%), followed by SRC (16% and 56%) and FRC (12% and 38%) (Figures 7 and 8).

At the biome scale, a positive $bWUE$ indicates that the system acts as a net C source per unit of water used, whereas a negative $bWUE$ indicates a net C sink. Overall, SN pasture maintained a

negative $bWUE$ throughout the study period, acting as a net C sink per unit of water used, while cane showed more variable behavior across growth cycles. Specifically, $bWUE$ was positive in PC, indicating a net C source per unit water used, and decreased progressively through FRC, approaching the values of IMP in SRC (Figure 9).

4 | Discussion

The conversion of pasture to cane reshaped water fluxes and WUE , though the direction and magnitude of these changes depended strongly on the land use to be replaced (Figure 10). ET in cane was lower than in IMP, driven by lower T. ET was higher in cane than SN, as both T and E were greater in cane than SN pasture. E accounted for a larger fraction of total water loss in cane than in either pasture type, indicating greater non-productive water use. Consistent with these patterns, cane exhibited a higher marginal water cost of C gain (lower g_l) and greater stomatal sensitivity to VPD (higher $|-m/b|$) than IMP, reflecting a more conservative yet VPD-responsive stomatal behavior in cane than IMP. Although the Oren model showed relatively low R^2 , its well-constrained parameters indicated that the derived stomatal sensitivity estimates were robust, supporting their use for complementary insights into water conservation strategies across land uses and study periods, consistent with findings elsewhere (Oren

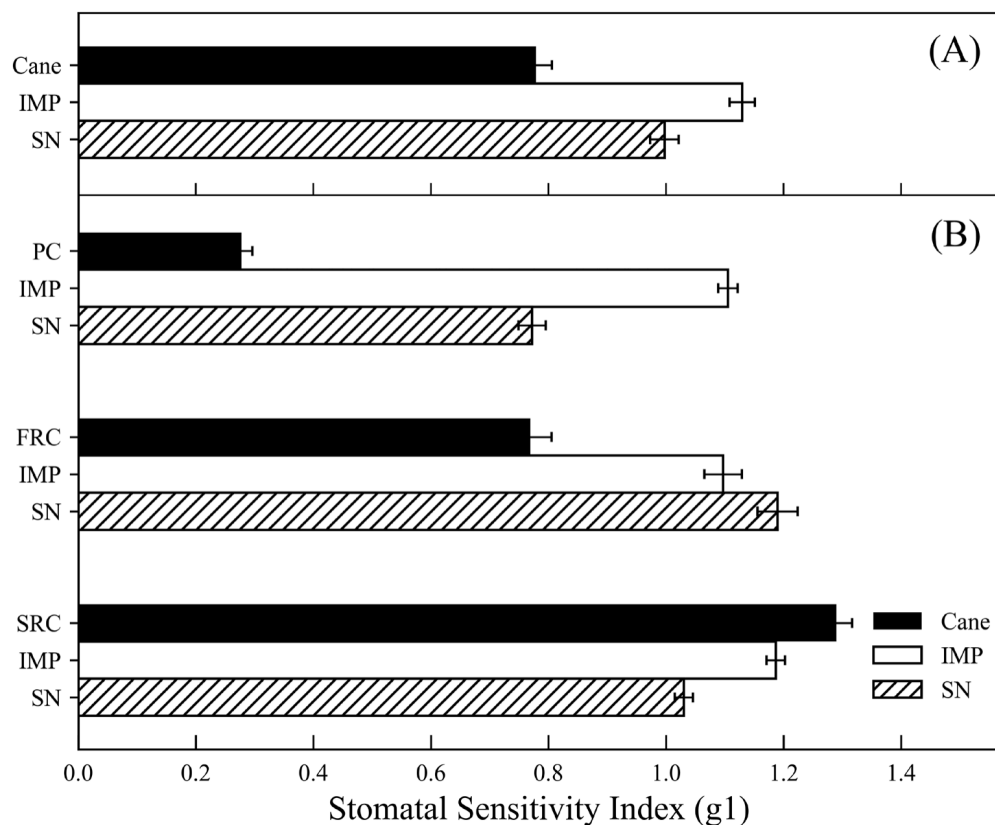


FIGURE 4 | Mean stomatal sensitivity index (g_1) and g_1 for sugarcane (cane), improved pasture (IMP), and semi-native pasture (SN) across the study period (A) and by year in 2019, 2020, 2021, and 2022 (B). G_1 reflects stomatal behavior in balancing C gain and T. PC was defined as sugarcane crop from planting until first harvest (here, from 2/6/2019 to 2/16/2020), FRC as cane crop from first to second harvest (here, from 2/17/2020 to 2/8/2021), and SRC as cane crop from second to third harvest (here, from 2/9/2021 to 4/6/2022). Overlapping uncertainty bounds between two land uses were interpreted as indicating similar g_1 magnitudes, while non-overlapping uncertainty bounds were interpreted as indicating meaningful differences between them.

et al. 1999; Sabot et al. 2022). In contrast, SN exhibited higher g_1 and lower $|m/b|$ than cane, indicating less conservative water use and weaker stomatal sensitivity to VPD. Despite these differences in stomatal strategy and E/T partitioning, cane exhibited greater WUE per unit of biomass and C assimilation than both pasture types, reflecting its higher photosynthetic capacity per unit water lost. Together our results suggest that the hydrological consequences of cane expansion differed markedly between the land use replaced: compared to IMP, cane showed modest reductions in ET with WUE gains, whereas compared to SN, cane drove substantially larger shifts in water balance with greater WUE improvements, but at the cost of increased non-productive water loss.

4.1 | Impact of Land Use Conversion on Water Use

Pasture-to-cane conversion can cause widely divergent ET responses, with reported decreases of 5% to increases of up to 30% (Hernandes et al. 2014; Hernandez et al. 2018; Anache et al. 2019), yet the drivers of this variability remain poorly understood largely due to the scarcity of multi-year field measurements with a mechanistic focus (Stoy et al. 2019; Feng et al. 2020; Chang et al. 2023). Our results showed that the type of pasture being displaced is a critical determinant of ET response to this

land conversion (Figure 10). The underlying mechanisms and implications are discussed below.

4.1.1 | Land Uses Exhibited Distinct Stomatal Regulation Pathways

Cane exhibited tighter stomatal regulation, stronger VPD sensitivity, lower T despite higher GPP (i.e., greater WUE), and lower g_s relative to IMP pasture (Figure 5 and Figure S4). This is consistent with a more conservative, isohydric-like water-use strategy compared to IMP, which exhibited a more anisohydric-like strategy (Oren et al. 1999). In other plant species, isohydric-like behavior has been associated with greater tolerance to increasing VPD and some degree of resilience under mild drought conditions (Chen et al. 2022; Hu, Ma, and Wang 2023; Hu, Sun, et al. 2023; Schumann et al. 2024). Given projected increases in VPD, our results suggest that cane is better adapted to tolerate increasing atmospheric water demand by limiting water loss and reducing the risk of hydraulic stress compared to IMP pasture; however, under prolonged or severe VPD increases, sustained stomatal closure may restrict C gain, potentially leading to reduced productivity and increased susceptibility to C starvation (Reyes et al. 2020; Cai et al. 2023).

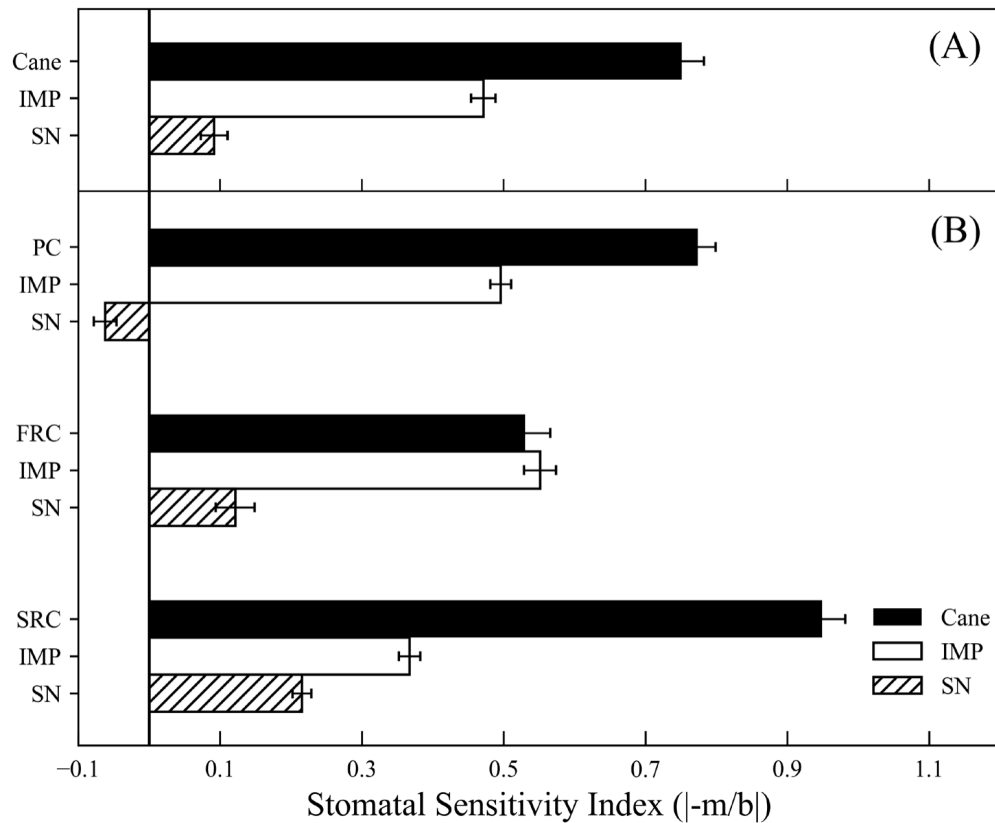


FIGURE 5 | Mean stomatal sensitivity index ($| -m/b |$) for sugarcane (cane), improved pasture (IMP), and semi-native pasture (SN) across the study period (A) and by year in 2019, 2020, 2021, and 2022 (B). The index reflects how rapid stomata closes and opens upon changes in VPD. PC was defined as sugarcane crop from planting until first harvest (here, from 2/6/2019 to 2/16/2020), FRC as cane crop from first to second harvest (here, from 2/17/2020 to 2/8/2021), and SRC as cane crop from second to third harvest (here, from 2/9/2021 to 4/6/2022). Overlapping uncertainty bounds between two land uses were interpreted as indicating similar index magnitudes, while non-overlapping uncertainty bounds were interpreted as indicating meaningful differences between them.

Unlike the isohydric-like stomatal response observed in cane, SN pasture exhibited lower T and g_s but weak stomatal sensitivity to VPD, consistent with its inherently low baseline g_s (Oren et al. 1999). Rather than reflecting differences in stomatal regulation strategy alone, this pattern may indicate site-specific hydrological and structural constraints. For instance, unlike IMP and cane, SN pastures lacked drainage ditches, resulting in longer inundation periods that may suppress root water uptake and limit T independent of stomatal regulation (Gomez-Casanovas et al. 2024).

The contrasting stomatal strategies identified across land uses (isohydric-like in cane, anisohydric-like in IMP, and baseline g_s -like in SN) likely represent a key determinant of the distinct pathways through which large-scale land use conversion may feedback on a changing climate (Basnayake et al. 2015; Anache et al. 2019; Baca Cabrera et al. 2021). By altering not only mean T but also its sensitivity to future atmospheric demand, these contrasting strategies will also mediate how each land use responds to projected increases in VPD.

The SN-to-cane displacement may carry further important thermal implications (Whitehead 1998; Buckley 2019; Miralles et al. 2025). Enhanced T and ET in cane relative to SN pasture implies higher LE flux, which may increase evaporative cooling

capacity following conversion, particularly during the heat waves projected to intensify under future climate scenarios (Mukherjee and Mishra 2021; Domeisen et al. 2023; Tripathy et al. 2023). This represents a fundamental trade-off. The greater water use in cane relative to SN pasture carries an evaporative cooling benefit, with large-scale conversion potentially moderating local and regional heat stress, though this benefit must be weighed against the increased water demand in what are often water-limited landscapes.

4.1.2 | Stand Age Is an Important Driver of T and Stomatal Regulation

As cane matured, g_1 increased, indicating a shift towards less conservative stomatal regulation (Figure 4). This resulted in stomata remaining open longer despite similar VPD across the study years (from 680 to 717 Pa across years), sustaining higher g_s and consequently greater T as the stand aged (Figure 4; Medlyn et al. 2011). This shift likely reflects the development of a more extensive and deeper root system as cane matures, facilitating access to deeper soil water, and reducing the sensitivity of leaf water status to high VPD and declining surface soil moisture (Gomez-Casanovas et al. 2024; Blanc-Betes et al. 2025). Consistent with observations in other crop species, by buffering

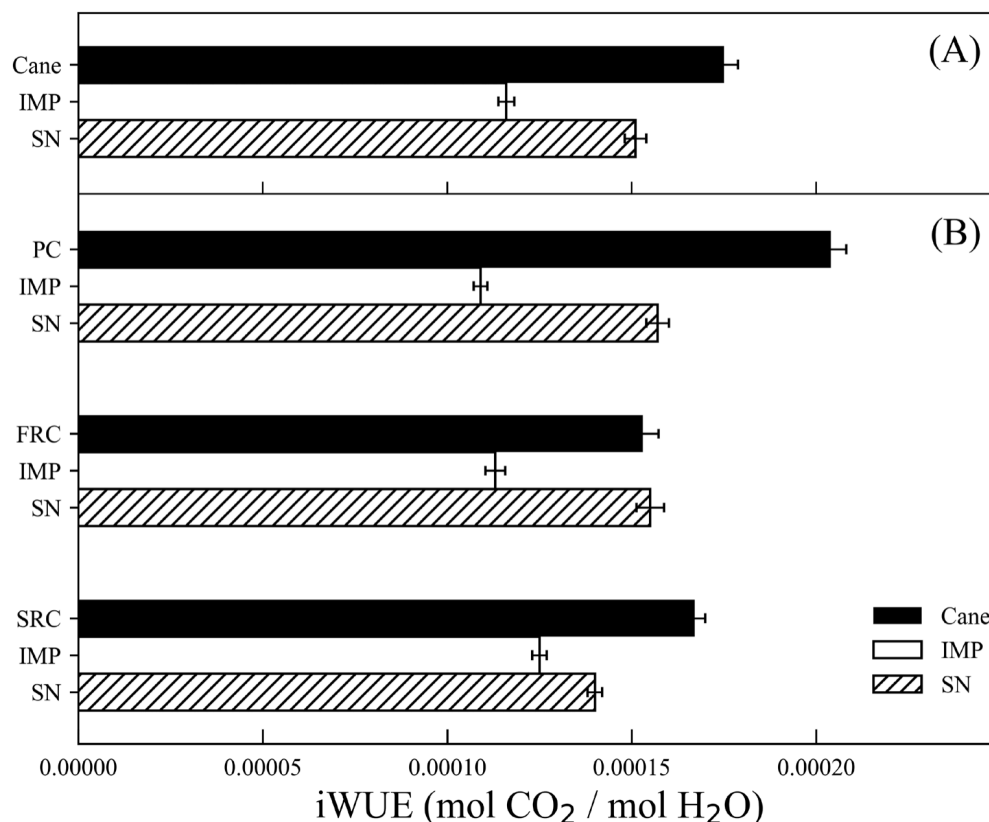


FIGURE 6 | Intrinsic Water Use Efficiency (iWUE) for sugarcane (cane), improved pasture (IMP), and semi-native pasture (SN) across the study period and by year in 2019, 2020, 2021, and 2022. PC defined from 2/6/2019 to 2/16/2020, FRC defined from 2/17/2020 to 2/8/2021, and SRC from 2/9/2021 to 4/6/2022. Overlapping uncertainty bounds between two land uses were interpreted as indicating similar WUE magnitudes, while non-overlapping uncertainty bounds were interpreted as indicating meaningful differences between them.

against short-term hydric stress, deeper rooting may allow mature cane to maintain higher water use under water limited conditions that would otherwise trigger stomatal closure (Lopes et al. 2011; Sutherlin et al. 2019; Chumphu et al. 2019).

Beyond rooting depth, age-related physiological changes may also contribute to enhanced T as cane matures (Table 1; Wang et al. 2018; Plett et al. 2020; Liao et al. 2022). Foliar nitrogen content tends to decline with canopy age in many plant species, and lower leaf nitrogen has been associated with weaker stomatal regulation and less conservative water use (Querejeta et al. 2022; Hu, Ma, and Wang 2023; Hu, Sun, et al. 2023; Khontiang et al. 2025). Age-related declines in stomatal regulation can persist even when nitrogen limitation is alleviated via fertilization, potentially reinforcing the shift in g_1 observed here (Tejera et al. 2022). Together, these results suggest that accounting for the impact of stand age on T in hydrological models is essential to accurately predict how cane-dominated bioenergy landscapes will affect the hydrological cycle in the Southeastern US.

Despite these mechanistic drivers, the T response to stand age was non-linear, declining from PC to FRC before recovering in SRC, following changes in $|m/b|$ (Table 1 and Figure 5). These patterns indicate that stomatal sensitivity to VPD was a key driver of interannual T variability (Grantz et al. 1987; Basnayake

et al. 2015; Tippayawat et al. 2023). These results imply that projected increases in VPD under climate change could increase T, particularly in older, less stomatal-conservative cane stands, with potential implications for landscape-scale water balances in the Southeastern US.

4.1.3 | Canopy Structure, Soil Exposure, and Root Functional Traits Govern E

E was higher in cane, likely driven by a combination of factors. First, taller canopies and higher g_a enhance turbulent gas exchange, accelerating the removal of water vapor from wet leaf surfaces, and both traits were higher in cane than in pastures (Figure S3; Marin et al. 2016; Green et al. 2021; Gomez-Casanovas et al. 2024). Second, periodic bare soil exposure during early establishment in PC and post-harvest phases in FRC and SRC can further enhance E relative to the continuously vegetated pasture surface (Olivier and Singels 2012; Gmach et al. 2019). Third, lower g_a in pastures likely restricted turbulent mixing near the soil surface, reducing the vapor pressure gradient driving soil evaporative flux and thereby limiting E compared to cane (Grantz 2013; Panwar et al. 2020). Fourth, considerably higher belowground productivity in IMP and SN may have promoted more rapid uptake of near-surface soil moisture, limiting water availability for soil E in pastures relative

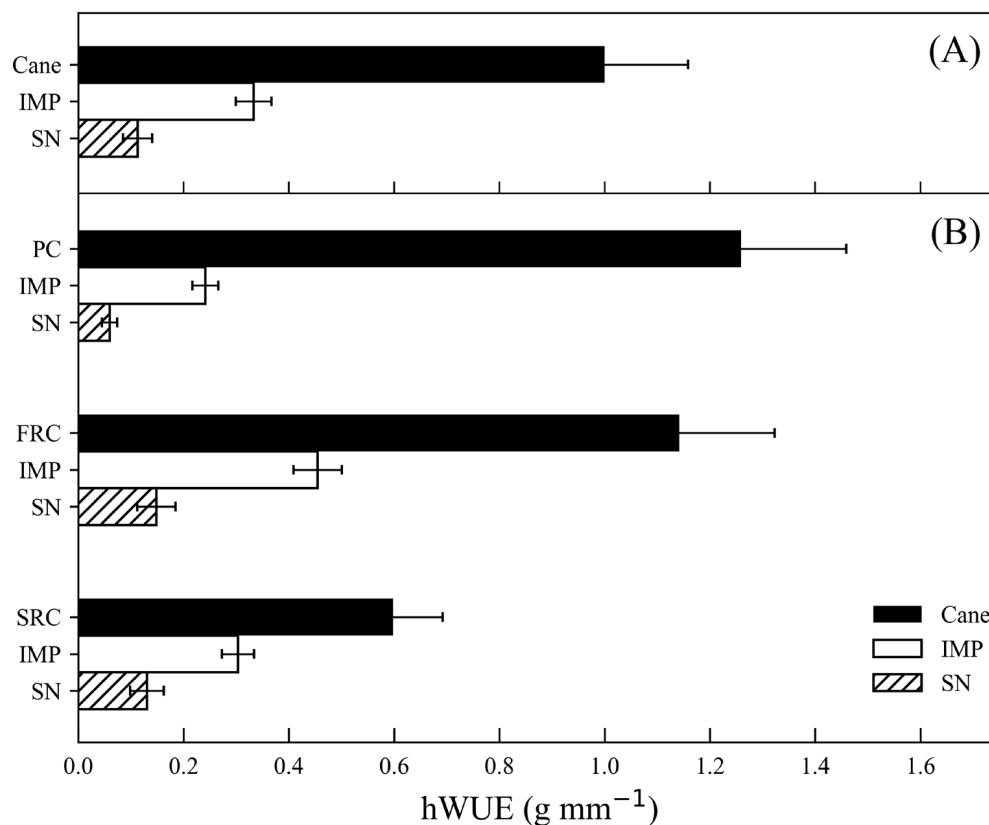


FIGURE 7 | Harvest Water Use Efficiency (hWUE) for sugarcane (cane), improved pasture (IMP), and semi-native pasture (SN) across the study period and by year in 2019, 2020, 2021, and 2022. PC defined from 2/6/2019 to 2/16/2020, FRC defined from 2/17/2020 to 2/8/2021, and SRC from 2/9/2021 to 4/6/2022. Overlapping uncertainty bounds between two land uses were interpreted as indicating similar WUE magnitudes, while non-overlapping uncertainty bounds were interpreted as indicating meaningful differences between them.

to cane, further reducing E (Kühnhammer et al. 2023; Demir et al. 2023; Blanc-Betes et al. 2025).

The higher E observed in cane relative to pastures represents a source of non-productive water loss that partially offsets the WUE gains associated with greater T and GPP. Targeted management practices could help reduce non-productive water losses and shift water use toward T, improving overall WUE. These include residue management strategies such as green cane harvesting or returning cane trash or bagasse to the fields to maintain soil cover (Olivier and Singels 2012; Dinesh et al. 2025), optimizing planting density and row spacing to promote rapid canopy closure (Olivier and Singels 2015; Fernandes et al. 2017), and integrating cover crops or intercrops to minimize bare soil exposure (Kaur et al. 2016; Singh et al. 2021).

4.2 | Water Use Efficiency (WUE)—From Canopy to Biome Scale

The impact of cane versus pastures on WUE varied with scale, with T dominating ET in cane, consistent with previous studies showing that T exerts a major control on WUE variability across ecosystems (Sun et al. 2023; Yang et al. 2025). These findings suggest that preserving stomatal sensitivity to VPD and efficient stomatal regulation in cane is a critical breeding and management target for maintaining WUE under intensifying drought and heat stress.

4.2.1 | Stomatal Regulation and Canopy Productivity Drive Higher Canopy and Ecosystem WUE in Cane

Higher iWUE (GPP/g_s) in cane relative to pasture indicated that cane fixed more C per unit of g_s , consistent with its more conservative stomatal strategy (Figure 6). This finding aligns with previous leaf-scale studies reporting higher iWUE in cane compared to other crop types (Ellsworth and White Jr. 2024; Lunn et al. 2024; Takaragawa et al. 2025). Rather than reflecting reduced photosynthetic capacity, higher iWUE stems from the ability of cane to maintain high GPP despite substantially lower g_s . This is supported by leaf-level stomatal physiology and anatomical traits including stomatal density, operational stomatal apertures, and guard cell potassium fluxes that enable sustained C gain at reduced g_s (Figure 6) (Israel et al. 2022; Heckman et al. 2024; Gomez-Casanovas et al. 2024; Ghannoum et al. 2025).

At the ecosystem scale, cane showed higher hWUE (harvest/ET) and eWUE (GPP/ET) than pastures (Figures 7 and 8), consistent with greater biomass production and GPP in cane (Gomez-Casanovas et al. 2024; Blanc-Betes et al. 2025). WUE advantages extended beyond the comparison with pastures, as both hWUE and eWUE in cane exceeded or were similar to values reported for other widely cultivated C4 bioenergy crops. For instance, in miscanthus (*Miscanthus* spp.), a leading cellulosic bioethanol crop, eWUE typically ranges from 0.3 to 1.31 $g\ m^{-2}\ mm^{-1}\ H_2O$ and hWUE values from 0.7 to 1.4 $g\ m^{-2}\ mm^{-1}\ H_2O$ (Zeri

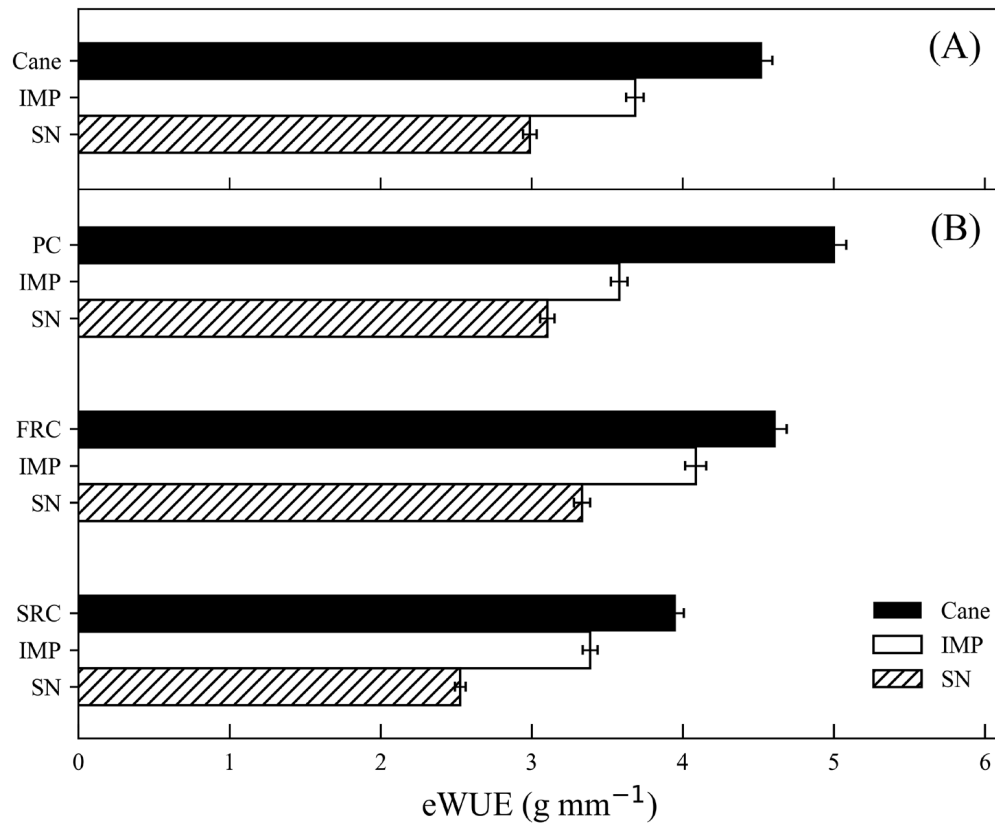


FIGURE 8 | Ecosystem Water Use Efficiency (eWUE) for sugarcane (cane), improved pasture (IMP), and semi-native pasture (SN) across the study period and by year in 2019, 2020, 2021, and 2022. PC defined from 2/6/2019 to 2/16/2020, FRC defined from 2/17/2020 to 2/8/2021, and SRC from 2/9/2021 to 4/6/2022. Overlapping uncertainty bounds between two land uses were interpreted as indicating similar WUE magnitudes, while non-overlapping uncertainty bounds were interpreted as indicating meaningful differences between them.

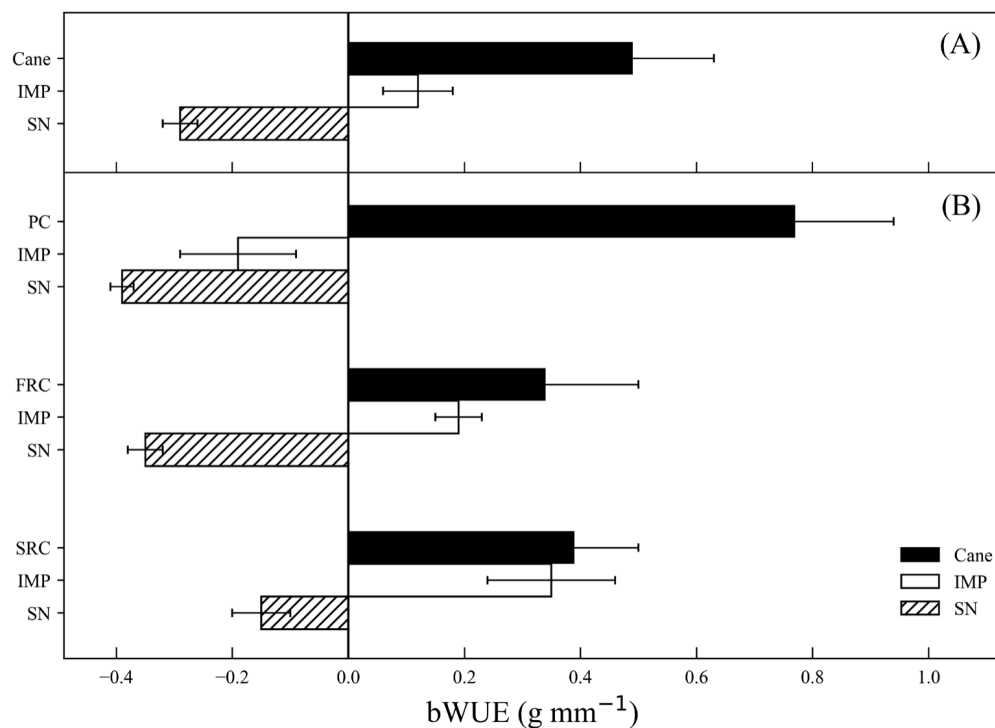


FIGURE 9 | Biome Water Use Efficiency (bWUE) for sugarcane (cane), improved pasture (IMP), and semi-native pasture (SN) across the study period and by year in 2019, 2020, 2021, and 2022. PC defined from 2/6/2019 to 2/16/2020, FRC defined from 2/17/2020 to 2/8/2021, and SRC from 2/9/2021 to 4/6/2022. Overlapping uncertainty bounds between two land uses were interpreted as indicating similar WUE magnitudes, while non-overlapping uncertainty bounds were interpreted as indicating meaningful differences between them.

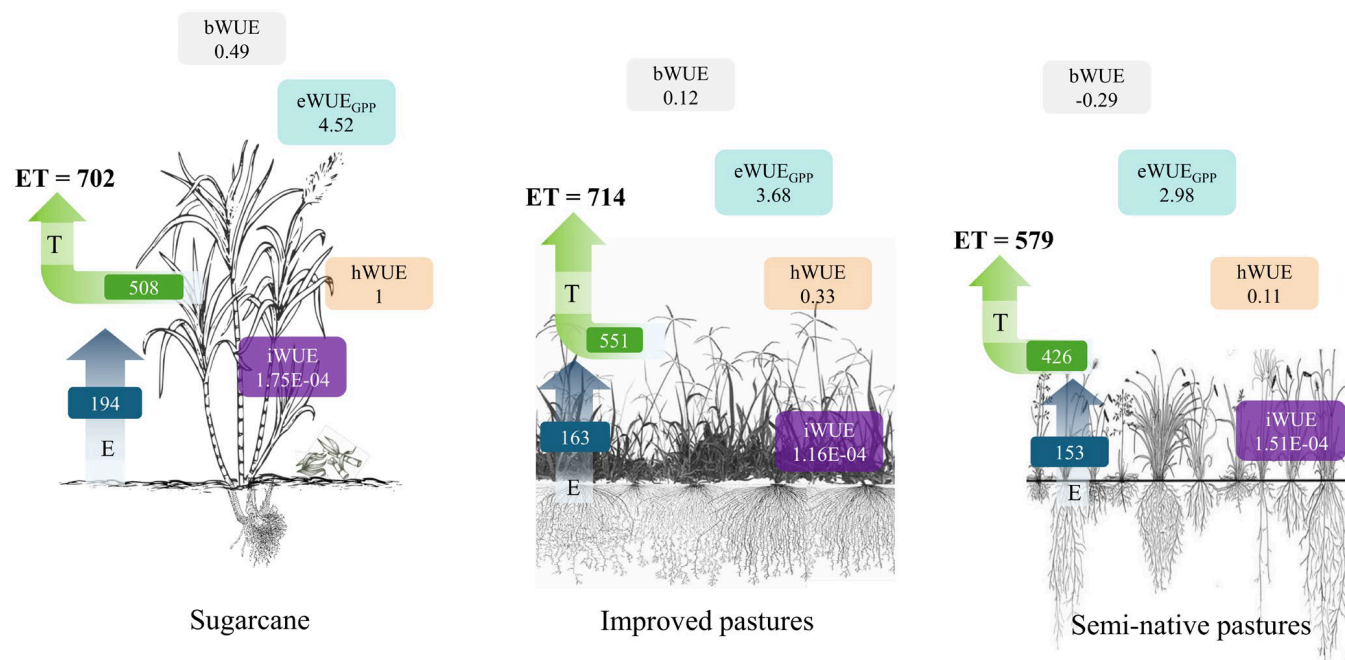


FIGURE 10 | Partial water cycle for sugarcane and improved (IMP) and semi-native (SN) pastures. Values are means for plant cane (from 2/6/2019 to 2/16/2020), first ratoon cane (from 2/17/2020 to 2/8/2021), and second ratoon cane (from 2/9/2021 to 4/6/2022) and corresponding periods for IMP and SN pastures. Values shown are evapotranspiration (ET), evaporation (E), and transpiration (T), alongside four WUE metrics: intrinsic WUE (iWUE; GPP per unit of stomatal water loss), harvest WUE (hWUE; harvested biomass per unit of ET), ecosystem WUE (eWUE; GPP per unit of ET), and biome WUE (bWUE; NECB per unit of ET, positive when the ecosystem acts as a C source and negative when it acts as a C sink).

et al. 2013; Maleski et al. 2019), values comparable to those observed in cane in the present study.

4.2.2 | Net Carbon Losses Rather Than Water Flux Govern Biome-Scale WUE Following Pasture Conversion

At the biome scale, net C losses following pasture conversion governed differences in water use and C retention between land uses, with cane showing lower efficiency in net C storage per unit water used than both pasture types. These results suggest that management strategies and breeding targeting enhanced C sequestration capacity can improve the C sink strength per unit water used, supporting more sustainable bioenergy production systems in the SE US.

In summary, large-scale conversion of IMP or SN pastures to cane produces widely contrasting hydrological outcomes. Relative to IMP pasture, cane exhibited a more conservative water-use strategy (i.e., lower g_1), consistent with rapid stomatal closure as VPD increased (i.e., higher $|-m/b|$) to limit water loss. Such stomatal regulation in cane may confer some tolerance to increasing atmospheric water demand, although severe or prolonged conditions could ultimately constrain T and C assimilation. As stands matured, however, stomata in cane became less conservative (i.e., higher g_1), yet more sensitive to VPD fluctuations (i.e., higher $|-m/b|$), underscoring the vulnerability of older cane stands to changes in VPD and the importance of incorporating stand age-dependent stomatal regulation into hydrological models for accurate predictions of cane expansion impacts. Across all WUE metrics, from the canopy to the ecosystem and

harvest-scale, cane delivered greater WUE than both pasture types. Nevertheless, higher E in cane relative to pastures represented a source of non-productive water loss partially offsetting these WUE gains. Minimizing E through targeted management practices such as residue management, while improving net C storage, will be essential to reconcile the trade-off between water expenditure and carbon retention in cane-based bioenergy systems. Overall, these findings highlight that the hydrological consequences of cane expansion across the Southeastern US will depend strongly on the type of pasture converted. The isohydric-like stomatal behavior in cane, whereby high g_s sensitivity to VPD triggers tight stomatal regulation and results in conservative water use, is likely to play a key role as a determinant of regional water balances under intensifying atmospheric water demand.

Author Contributions

Elena Blanc-Betes: conceptualization, investigation, formal analysis, data curation, writing – review and editing, methodology, validation. **Sneha Bandyopadhyay:** investigation, writing – original draft, validation, visualization, writing – review and editing, formal analysis, data curation, methodology. **Amartya Saha:** investigation, resources, writing – review and editing. **Carl J. Bernacchi:** conceptualization, funding acquisition, writing – review and editing, resources. **Evan H. DeLucia:** conceptualization, funding acquisition, writing – review and editing, resources. **Caitlin E. Moore:** investigation, writing – review and editing, conceptualization. **Cole Walton:** writing – original draft, writing – review and editing, methodology, validation, formal analysis. **Elizabeth H. Boughton:** conceptualization, funding acquisition, writing – review and editing, resources. **Nuria Gomez-Casanovas:** conceptualization, investigation, funding acquisition, methodology,

validation, writing – review and editing, supervision, data curation.
Wendy H. Yang: conceptualization, funding acquisition, writing – review and editing.
Tess Rutstein: validation, writing – review and editing, formal analysis, data curation.

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data that support the findings of this study are openly available in Figshare at <https://doi.org/10.6084/m9.figshare.32411850>.

References

Abraha, M., J. Chen, H. Chu, et al. 2015. "Evapotranspiration of Annual and Perennial Biofuel Crops in a Variable Climate." *GCB Bioenergy* 7, no. 6: 1344–1356. <https://doi.org/10.1111/gcbb.12239>.

Alavi, M., M. Albaji, M. Golabi, A. A. Naseri, and S. Homayouni. 2024. "Estimation of Sugarcane Evapotranspiration From Remote Sensing and Limited Meteorological Variables Using Machine Learning Models." *Journal of Hydrology* 629: 130605. <https://doi.org/10.1016/j.jhydrol.2023.130605>.

Anache, J. A., E. Wendland, L. M. Rosalem, C. Youlton, and P. T. Oliveira. 2019. "Hydrological Trade-Offs due to Different Land Covers and Land

Uses in the Brazilian Cerrado." *Hydrology and Earth System Sciences* 23, no. 3: 1263–1279. <https://doi.org/10.5194/hess-23-1263-2019>.

Anapalli, S. S., D. K. Fisher, K. N. Reddy, J. L. Krutz, S. R. Pinnamaneni, and R. Sui. 2019. "Quantifying Water and CO₂ Fluxes and Water Use Efficiencies Across Irrigated C3 and C4 Crops in a Humid Climate." *Science of the Total Environment* 663: 338–350. <https://doi.org/10.1016/j.scitotenv.2018.12.471>.

Anderson, R. G., D. Wang, R. Tirado-Corbalá, H. Zhang, and J. E. Ayars. 2015. "Divergence of Actual and Reference Evapotranspiration Observations for Irrigated Sugarcane With Windy Tropical Conditions." *Hydrology and Earth System Sciences* 19, no. 1: 583–599. <https://doi.org/10.5194/hess-19-583-2015>.

Arneth, A., J. Lloyd, H. Šantrůčková, et al. 2002. "Response of Central Siberian Scots Pine to Soil Water Deficit and Long-Term Trends in Atmospheric CO₂ Concentration." *Global Biogeochemical Cycles* 16, no. 1: 5–1–5–13. <https://doi.org/10.1029/2000GB001374>.

Aubinet, M., T. Vesala, and D. Papale, eds. 2012. *Eddy Covariance: A Practical Guide to Measurement and Data Analysis*. Springer Science & Business Media. <https://doi.org/10.1007/978-94-007-2351-1>.

Baca Cabrera, J. C., R. T. Hirl, R. Schäufele, A. Macdonald, and H. Schnyder. 2021. "Stomatal Conductance Limited the CO₂ Response of Grassland in the Last Century." *BMC Biology* 19, no. 1: 50. <https://doi.org/10.1186/s12915-021-00988-4>.

Baldocchi, D. 2014. "Measuring Fluxes of Trace Gases and Energy Between Ecosystems and the Atmosphere—the State and Future of the Eddy Covariance Method." *Global Change Biology* 20, no. 12: 3600–3609. <https://doi.org/10.1111/gcb.12649>.

Baldocchi, 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://doi.org/10.1175/1520-0477\(2001\)082<2415:FANTTS>2.3.CO;2](https://doi.org/10.1175/1520-0477(2001)082<2415:FANTTS>2.3.CO;2).

Baldocchi, D., and T. Meyers. 1998. "On Using Eco-Physiological, Micrometeorological and Biogeochemical Theory to Evaluate Carbon Dioxide, Water Vapor and Trace Gas Fluxes Over Vegetation: A Perspective." *Agricultural and Forest Meteorology* 90, no. 1–2: 1–25. [https://doi.org/10.1016/S0168-1923\(97\)00072-5](https://doi.org/10.1016/S0168-1923(97)00072-5).

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://doi.org/10.1111/gcb.14807>.

Baldocchi, D. D., K. B. Wilson, and L. Gu. 2002. "How the Environment, Canopy Structure and Canopy Physiological Functioning Influence Carbon, Water and Energy Fluxes of a Temperate Broad-Leaved Deciduous Forest—An Assessment With the Biophysical Model CANOAK." *Tree Physiology* 22, no. 15–16: 1065–1077. <https://doi.org/10.1093/treephys/22.15-16.1065>.

Basnayake, J., P. A. Jackson, N. G. Inman-Bamber, and P. Lakshmanan. 2015. "Sugarcane for Water-Limited Environments. Variation in Stomatal Conductance and Its Genetic Correlation With Crop Productivity." *Journal of Experimental Botany* 66, no. 13: 3945–3958. <https://doi.org/10.1093/jxb/erv194>.

Bispo, R. C., F. B. T. Hernandez, I. Z. Gonçalves, C. M. U. Neale, and A. H. C. Teixeira. 2022. "Remote Sensing-Based Evapotranspiration Modeling for Sugarcane in Brazil Using a Hybrid Approach." *Agricultural Water Management* 271: 107763. <https://doi.org/10.1016/j.agwat.2022.107763>.

Blanc-Betes, E., N. Gomez-Casanovas, C. J. Bernacchi, E. H. Boughton, W. Yang, and E. H. DeLucia. 2025. "The Carbon Budget of Land Conversion: Sugarcane Expansion and Implications for a Sustainable Bioenergy Landscape in Southeastern United States." *GCB Bioenergy* 17, no. 7: e70058. <https://doi.org/10.1111/gcbb.70058>.

Boughton, E. H., N. Gomez-Casanovas, H. Swain, et al. 2022. "Patch-Burn Grazing Impacts Forage Resources in Subtropical Humid Grazing

- Lands." *Rangeland Ecology & Management* 84: 10–21. <https://doi.org/10.1016/j.rama.2022.05.004>.
- Buckley, T. N. 2019. "How Do Stomata Respond to Water Status?" *New Phytologist* 224, no. 1: 21–36. <https://doi.org/10.1111/nph.15899>.
- Cabral, O. M., H. R. Rocha, J. H. Gash, et al. 2012. "Water Use in a Sugarcane Plantation." *GCB Bioenergy* 4, no. 5: 555–565. <https://doi.org/10.1111/j.1757-1707.2011.01155.x>.
- Cai, G., A. Carminati, S. M. Gleason, M. Javaux, and M. A. Ahmed. 2023. "Soil–Plant Hydraulics Explain Stomatal Efficiency–Safety Tradeoff." *Plant, Cell & Environment* 46, no. 10: 3120–3127. <https://doi.org/10.1111/pce.14536>.
- Carvalho, H. D., A. M. Howard, C. R. Crozier, et al. 2024. "Water Use and Radiation Balance of Miscanthus and Corn on Marginal Land in the Coastal Plain Region of North Carolina." *GCB Bioenergy* 16, no. 8: e13182. <https://doi.org/10.1111/gcbb.13182>.
- Celis, J., X. Xiao, P. M. White Jr., O. M. Cabral, and H. C. Freitas. 2023. "Improved Modeling of Gross Primary Production and Transpiration of Sugarcane Plantations With Time-Series Landsat and Sentinel-2 Images." *Remote Sensing* 16, no. 1: 46. <https://doi.org/10.3390/rs16010046>.
- Chamberlain, S. D., P. M. Groffman, E. H. Boughton, et al. 2017. "The Impact of Water Management Practices on Subtropical Pasture Methane Emissions and Ecosystem Service Payments." *Ecological Applications* 27, no. 4: 1199–1209. <https://doi.org/10.1002/eap.1514>.
- Chang, Y., Y. Ding, S. Zhang, J. Qin, and Q. Zhao. 2023. "Variations and Drivers of Evapotranspiration in the Tibetan Plateau During 1982–2015." *Journal of Hydrology: Regional Studies* 47: 101366. <https://doi.org/10.1016/j.ejrh.2023.101366>.
- Chen, W., S. Liu, S. Zhao, et al. 2023. "Temporal Dynamics of Ecosystem, Inherent, and Underlying Water Use Efficiencies of Forests, Grasslands, and Croplands and Their Responses to Climate Change." *Carbon Balance and Management* 18, no. 1: 13. <https://doi.org/10.1186/s13021-023-00232-2>.
- Chen, Z., S. Li, X. Wan, and S. Liu. 2022. "Strategies of Tree Species to Adapt to Drought From Leaf Stomatal Regulation and Stem Embolism Resistance to Root Properties." *Frontiers in Plant Science* 13: 926535. <https://doi.org/10.3389/fpls.2022.926535>.
- Chukalla, A. D., M. M. Mekonnen, D. Gunathilake, F. T. Wolkeba, B. Gunasekara, and D. Vanham. 2025. "Global Spatially Explicit Crop Water Consumption Shows an Overall Increase of 9% for 46 Agricultural Crops From 2010 to 2020." *Nature Food* 6, no. 10: 983–994. <https://doi.org/10.1038/s43016-025-01231-x>.
- Chumphu, S., N. Jongrunklang, and P. Songsri. 2019. "Association of Physiological Responses and Root Distribution Patterns of Ratooning Ability and Yield of the Second Ratoon Cane in Sugarcane Elite Clones." *Agronomy* 9, no. 4: 200. <https://doi.org/10.3390/agronomy9040200>.
- Collatz, G. J., J. T. Ball, C. Grivet, and J. A. Berry. 1991. "Physiological and Environmental Regulation of Stomatal Conductance, Photosynthesis and Transpiration: A Model That Includes a Laminar Boundary Layer." *Agricultural and Forest Meteorology* 54, no. 2–4: 107–136. [https://doi.org/10.1016/0168-1923\(91\)90002-8](https://doi.org/10.1016/0168-1923(91)90002-8).
- Cowan, I. R., and G. D. Farquhar. 1977. "Stomatal Function in Relation to Leaf Metabolism and Environment: Stomatal Function in the Regulation of Gas Exchange." In *Symposium of the Society of Experimental Botany*, edited by D. H. Jennings, vol. 31, 471–505. Cambridge University Press.
- De Kauwe, M. G., S. X. Zhou, B. E. Medlyn, et al. 2015. "Do Land Surface Models Need to Include Differential Plant Species Responses to Drought? Examining Model Predictions Across a Mesic-Xeric Gradient in Europe." *Biogeosciences* 12, no. 24: 7503–7518. <https://doi.org/10.5194/bg-12-7503-2015>.
- Demir, G., A. J. Guswa, J. Filipzik, J. C. Metzger, C. Römermann, and A. Hildebrandt. 2023. "Root Water Uptake Patterns Are Controlled by Tree Species Interactions and Soil Water Variability." *Hydrology and Earth System Sciences Discussions* 2023: 1–41. <https://doi.org/10.5194/hess-28-1441-2024>.
- Dertli, H. I., D. B. Hayes, and T. G. Zorn. 2024. "Effects of Multicollinearity and Data Granularity on Regression Models of Stream Temperature." *Journal of Hydrology* 639: 131572. <https://doi.org/10.1016/j.jhydrol.2024.131572>.
- Dinesh, G. K., M. Sinduja, K. S. K. Sri, et al. 2025. "Impact of Climate Change on Sugarcane: Mitigation and Adaptation Strategies." In *Climate-Smart Sugarcane Cultivation*, 69–113. Apple Academic Press.
- Dixon, A. P., D. Faber-Langendoen, C. Josse, J. Morrison, and C. J. Loucks. 2014. "Distribution Mapping of World Grassland Types." *Journal of Biogeography* 41, no. 11: 2003–2019. <https://doi.org/10.1111/jbi.12381>.
- Domeisen, D. I., E. A. Eltahir, E. M. Fischer, et al. 2023. "Prediction and Projection of Heatwaves." *Nature Reviews Earth & Environment* 4, no. 1: 36–50. <https://doi.org/10.1038/s43017-022-00371-z>.
- Dong, X., G. Dong, J. Chen, et al. 2024. "Reclamation Alters Evapotranspiration and Its Biophysical Controls in a Meadow Grassland on the Mongolian Plateau." *Journal of Environmental Management* 370: 122528. <https://doi.org/10.1016/j.jenvman.2024.122528>.
- Eichelmann, E., C. Wagner-Riddle, J. Warland, B. Deen, and P. Voroney. 2016. "Evapotranspiration, Water Use Efficiency, and Energy Partitioning of a Mature Switchgrass Stand." *Agricultural and Forest Meteorology* 217: 108–119. <https://doi.org/10.1016/j.agrformet.2015.11.008>.
- El-Araby, R. 2024. "Biofuel Production: Exploring Renewable Energy Solutions for a Greener Future." *Biotechnology for Biofuels and Bioproducts* 17, no. 1: 129. <https://doi.org/10.1186/s13068-024-02571-9>.
- Ellsworth, P. Z., and P. M. White Jr. 2024. "Carbon Isotopic Composition Reflects Intrinsic Water Use Efficiency but Not Its Component Traits in Sugarcane." *Tropical Plant Biology* 17: 306–315. <https://doi.org/10.1007/s12042-024-09367-z>.
- Farmland Information Center. 2022. "FIC." <https://farmlandinfo.org/>.
- Farquhar, G. D., S. V. von Caemmerer, and J. A. Berry. 1980. "A Biochemical Model of Photosynthetic CO₂ Assimilation in Leaves of C3 Species." *Planta* 149, no. 1: 78–90. <https://doi.org/10.1007/BF00386231>.
- Feng, S., J. Liu, Q. Zhang, et al. 2020. "A Global Quantification of Factors Affecting Evapotranspiration Variability." *Journal of Hydrology* 584: 124688. <https://doi.org/10.1016/j.jhydrol.2020.124688>.
- Fernandes, R. P., R. W. da Costa Silva, L. F. Salemi, et al. 2017. "The Influence of Sugarcane Crop Development on Rainfall Interception Losses." *Journal of Hydrology* 551: 532–539. <https://doi.org/10.1016/j.jhydrol.2017.06.027>.
- Foken, T., M. Göckede, M. Mauder, L. Mahrt, B. Amiro, and W. Munger. 2004. "Post-Field Data Quality Control." In *Handbook of Micrometeorology*. Atmospheric and Oceanographic Sciences Library, edited by X. Lee, W. Massman, and B. Law, vol. 29. Springer. https://doi.org/10.1007/1-4020-2265-4_9.
- Fuss, S., J. G. Canadell, G. P. Peters, et al. 2014. "Betting on Negative Emissions." *Nature Climate Change* 4, no. 10: 850–853. <https://doi.org/10.1038/nclimate2392>.
- Ghannoum, O., Y. M. Al-Salman, and F. J. Cano. 2025. "Opportunities for Improving Intrinsic Water Use Efficiency in C4 Plants Under Climate Change." *New Phytologist* 248, no. 6: 2656–2673. <https://doi.org/10.1111/nph.70660>.
- Gmach, M. R., F. V. Scarpere, M. R. Cherubin, et al. 2019. "Sugarcane Straw Removal Effects on Soil Water Storage and Drainage in Southeastern Brazil." *Journal of Soil and Water Conservation* 74, no. 5: 466–476. <https://doi.org/10.2489/jswc.74.5.466>.

- Gomez-Casanovas, N., E. Blanc-Betes, C. J. Bernacchi, et al. 2024. "Impact of Sugarcane Cultivation on C Cycling in Southeastern United States Following Conversion From Grazed Pastures." *GCB Bioenergy* 16, no. 10: e70003. <https://doi.org/10.1111/gcbb.70003>.
- Gomez-Casanovas, N., N. J. DeLucia, C. J. Bernacchi, et al. 2018. "Grazing Alters Net Ecosystem C Fluxes and the Global Warming Potential of a Subtropical Pasture." *Ecological Applications* 28, no. 2: 557–572. <https://doi.org/10.1002/eap.1670>.
- Gomez-Casanovas, N., N. J. DeLucia, E. H. DeLucia, et al. 2020. "Seasonal Controls of CO₂ and CH₄ Dynamics in a Temporarily Flooded Subtropical Wetland." *Journal of Geophysical Research: Biogeosciences* 125, no. 3: e2019JG005257. <https://doi.org/10.1029/2019JG005257>.
- Grantz, D. A. 2013. "Water, Transpiration, and Gas Exchange." In *Sugarcane: Physiology, Biochemistry, and Functional Biology*, 221–254. Wiley. <https://doi.org/10.1002/9781118771280.ch10>.
- Grantz, D. A., P. H. Moore, and E. Zeiger. 1987. "Stomatal Responses to Light and Humidity in Sugarcane: Prediction of Daily Time Courses and Identification of Potential Selection Criteria." *Plant, Cell & Environment* 10, no. 3: 197–204. <https://doi.org/10.1111/1365-3040.ep11602231>.
- Green, A., G. Bohrer, and R. Petrone. 2021. "Microclimatic Effects of a Forest-To-Peatland Transition on Aerodynamic Resistance to Water Vapour Transfer in the Sub-Humid Boreal Plains." *Boundary-Layer Meteorology* 178, no. 2: 301–322. <https://doi.org/10.1007/s10546-020-00572-3>.
- Grossiord, C., T. N. Buckley, L. A. Cernusak, et al. 2020. "Plant Responses to Rising Vapor Pressure Deficit." *New Phytologist* 226, no. 6: 1550–1566. <https://doi.org/10.1111/nph.16485>.
- Han, T., Q. Feng, T. Yu, et al. 2023. "Contrasting Response of Water Use Efficiency to Soil Moisture Availability: From Leaf to Ecosystem in an Arid Oasis." *Ecological Indicators* 147: 109964. <https://doi.org/10.1016/j.ecolind.2023.109964>.
- Haverd, V., B. Smith, L. Nieradzki, et al. 2018. "A New Version of the CABLE Land Surface Model (Subversion Revision r4601) Incorporating Land Use and Land Cover Change, Woody Vegetation Demography, and a Novel Optimisation-Based Approach to Plant Coordination of Photosynthesis." *Geoscientific Model Development* 11, no. 7: 2995–3026. <https://doi.org/10.5194/gmd-11-2995-2018>.
- Heckman, R. W., C. G. Pereira, M. J. Aspinwall, and T. E. Juenger. 2024. "Physiological Responses of C4 Perennial Bioenergy Grasses to Climate Change: Causes, Consequences, and Constraints." *Annual Review of Plant Biology* 75: 737–769. <https://doi.org/10.1146/annurev-arplant-070623-093952>.
- Hernandes, T. A. D., V. B. Bufon, and J. E. Seabra. 2014. "Water Footprint of Biofuels in Brazil: Assessing Regional Differences." *Biofuels, Bioproducts & Biorefining* 8, no. 2: 241–252. <https://doi.org/10.1002/bbb.1454>.
- Hernandes, T. A. D., F. V. Scarpere, and J. E. A. Seabra. 2018. "Assessment of the Recent Land Use Change Dynamics Related to Sugarcane Expansion and the Associated Effects on Water Resources Availability." *Journal of Cleaner Production* 197: 1328–1341. <https://doi.org/10.1016/j.jclepro.2018.06.297>.
- Hoover, D. L., L. J. Abendroth, D. M. Browning, et al. 2023. "Indicators of Water Use Efficiency Across Diverse Agroecosystems and Spatiotemporal Scales." *Science of the Total Environment* 864: 160992. <https://doi.org/10.1016/j.scitotenv.2022.160992>.
- Hou, Y., M. Zhang, X. Wei, et al. 2020. "Quantification of Ecohydrological Sensitivities and Their Influencing Factors at the Seasonal Scale." *Hydrology and Earth System Sciences Discussions*: 1–31. <https://doi.org/10.5194/hess-25-1447-2021>.
- Hsieh, C. I., G. Katul, and T. W. Chi. 2000. "An Approximate Analytical Model for Footprint Estimation of Scalar Fluxes in Thermally Stratified Atmospheric Flows." *Advances in Water Resources* 23, no. 7: 765–772. [https://doi.org/10.1016/S0309-1708\(99\)00042-1](https://doi.org/10.1016/S0309-1708(99)00042-1).
- Hu, J., W. Ma, and Z. Wang. 2023. "Effects of Nitrogen Addition and Drought on the Relationship Between Nitrogen-and Water-Use Efficiency in a Temperate Grassland." *Ecological Processes* 12, no. 1: 36. <https://doi.org/10.1186/s13717-023-00448-7>.
- Hu, Y., Z. Sun, Y. Zeng, et al. 2023. "Tree-Level Stomatal Regulation Is More Closely Related to Xylem Hydraulic Traits Than to Leaf Photosynthetic Traits Across Diverse Tree Species." *Agricultural and Forest Meteorology* 329: 109291. <https://doi.org/10.1016/j.agrformet.2022.109291>.
- Hu, Z., G. Yu, Y. Zhou, et al. 2009. "Partitioning of Evapotranspiration and Its Controls in Four Grassland Ecosystems: Application of a Two-Source Model." *Agricultural and Forest Meteorology* 149, no. 9: 1410–1420. <https://doi.org/10.1016/j.agrformet.2009.03.014>.
- Hudiburg, T. W., W. Wang, M. Khanna, et al. 2016. "Impacts of a 32-Billion-Gallon Bioenergy Landscape on Land and Fossil Fuel Use in the US." *Nature Energy* 1, no. 1: 1–7. <https://doi.org/10.1038/nenergy.2015.5>.
- Inman-Bamber, N. G., P. Lakshmanan, and S. Park. 2012. "Sugarcane for Water-Limited Environments: Theoretical Assessment of Suitable Traits." *Field Crops Research* 134: 95–104. <https://doi.org/10.1016/j.fcr.2012.05.004>.
- Isaac, P., J. Cleverly, I. McHugh, E. Van Gorsel, C. Ewenz, and J. Beringer. 2017. "OzFlux Data: Network Integration From Collection to Curation." *Biogeosciences* 14, no. 12: 2903–2928. <https://doi.org/10.5194/bg-14-2903-2017>.
- Israel, W. K., A. Watson-Lazowski, Z. H. Chen, and O. Ghannoum. 2022. "High Intrinsic Water Use Efficiency Is Underpinned by High Stomatal Aperture and Guard Cell Potassium Flux in C3 and C4 Grasses Grown at Glacial CO₂ and Low Light." *Journal of Experimental Botany* 73, no. 5: 1546–1565. <https://doi.org/10.1093/jxb/erab477>.
- Jarvis, P. G. 1980. "Stomatal Response to Water Stress in Conifers." In *Adaptation of Plants to Water and High Temperature Stress*, edited by N. C. Turner and P. J. Kramer, 105–122. John Wiley & Sons.
- Jian, J., V. Bailey, K. Dorheim, et al. 2022. "Historically Inconsistent Productivity and Respiration Fluxes in the Global Terrestrial Carbon Cycle." *Nature Communications* 13, no. 1: 1733. <https://doi.org/10.1038/s41467-022-29391-5>.
- Katul, G., S. Manzoni, S. Palmroth, and R. Oren. 2010. "A Stomatal Optimization Theory to Describe the Effects of Atmospheric CO₂ on Leaf Photosynthesis and Transpiration." *Annals of Botmonteithany* 105, no. 3: 431–442. <https://doi.org/10.1093/aob/mcp292>.
- Kaur, N., M. S. Bhullar, and G. Gill. 2016. "Weed Management in Sugarcane-Canola Intercropping Systems in Northern India." *Field Crops Research* 188: 1–9. <https://doi.org/10.1016/j.fcr.2016.01.009>.
- Kelliher, F. M., R. Leuning, M. R. Raupach, and E. D. Schulze. 1995. "Maximum Conductances for Evaporation From Global Vegetation Types." *Agricultural and Forest Meteorology* 73, no. 1–2: 1–16. [https://doi.org/10.1016/0168-1923\(94\)02178-M](https://doi.org/10.1016/0168-1923(94)02178-M).
- Khontiang, K., D. Ketrot, S. Tawornpruek, C. Wongleecharoen, T. Inboonchuay, and A. Wongsuksri. 2025. "Influence of Foliar and Soil Potassium Fertilizer on Ratoon Sugarcane Performance: Yield, Quality, and Nutrient Uptake." *Frontiers in Soil Science* 5: 1502972. <https://doi.org/10.3389/fsoil.2025.1502972>.
- Knauer, J., T. S. El-Madany, S. Zaehle, and M. Migliavacca. 2018. "Bingleaf—An R Package for the Calculation of Physical and Physiological Ecosystem Properties From Eddy Covariance Data." *PLoS One* 13, no. 8: e0201114. <https://doi.org/10.1371/journal.pone.0201114>.
- Knauer, J., T. Wutzler, A. Bennett, S. Zaehle, T. El-Madany, and M. Migliavacca. 2022. "Bingleaf: Physical and Physiological Ecosystem Properties From Eddy Covariance Data."

- Kühnhammer, K., J. van Haren, A. Kübert, et al. 2023. "Deep Roots Mitigate Drought Impacts on Tropical Trees Despite Limited Quantitative Contribution to Transpiration." *Science of the Total Environment* 893: 164763. <https://doi.org/10.1016/j.scitotenv.2023.164763>.
- Lange, O. L., R. Lösch, E. D. Schulze, and L. Kappen. 1971. "Responses of Stomata to Changes in Humidity." *Planta* 100, no. 1: 76–86. <https://doi.org/10.1007/BF00386887>.
- Lawrence, D. M., R. A. Fisher, C. D. Koven, et al. 2019. "The Community Land Model Version 5: Description of New Features, Benchmarking, and Impact of Forcing Uncertainty." *Journal of Advances in Modeling Earth Systems* 11, no. 12: 4245–4287. <https://doi.org/10.1029/2018MS001583>.
- Liao, Q., R. Ding, T. Du, S. Kang, L. Tong, and S. Li. 2022. "Stomatal Conductance Drives Variations of Yield and Water Use of Maize Under Water and Nitrogen Stress." *Agricultural Water Management* 268: 107651. <https://doi.org/10.1016/j.agwat.2022.107651>.
- Lin, Y. S., B. E. Medlyn, R. A. Duursma, et al. 2015. "Optimal Stomatal Behaviour Around the World." *Nature Climate Change* 5, no. 5: 459–464. <https://doi.org/10.1038/nclimate2550>.
- Lopes, M. S., J. L. Araus, P. D. Van Heerden, and C. H. Foyer. 2011. "Enhancing Drought Tolerance in C4 Crops." *Journal of Experimental Botany* 62, no. 9: 3135–3153. <https://doi.org/10.1093/jxb/err105>.
- Lunn, D., B. Kannan, A. Germon, et al. 2024. "Greater Aperture Counteracts Effects of Reduced Stomatal Density on Water Use Efficiency: A Case Study on Sugarcane and Meta-Analysis." *Journal of Experimental Botany* 75, no. 21: 6837–6849. <https://doi.org/10.1093/jxb/erae271>.
- Maleski, J. J., D. D. Bosch, R. G. Anderson, A. W. Coffin, W. F. Anderson, and T. C. Strickland. 2019. "Evaluation of Miscanthus Productivity and Water Use Efficiency in Southeastern United States." *Science of the Total Environment* 692: 1125–1134. <https://doi.org/10.1016/j.scitotenv.2019.07.128>.
- Marin, F. R., L. R. Angelocci, D. S. Nassif, L. G. Costa, M. S. Vianna, and K. S. Carvalho. 2016. "Crop Coefficient Changes With Reference Evapotranspiration for Highly Canopy-Atmosphere Coupled Crops." *Agricultural Water Management* 163: 139–145. <https://doi.org/10.1016/j.agwat.2015.09.010>.
- Medlyn, B. E., R. A. Duursma, D. Eamus, et al. 2011. "Reconciling the Optimal and Empirical Approaches to Modelling Stomatal Conductance." *Global Change Biology* 17, no. 6: 2134–2144. <https://doi.org/10.1111/j.1365-2486.2010.02375.x>.
- Meinshausen, N., and G. Ridgeway. 2006. "Quantile Regression Forests." *Journal of Machine Learning Research* 7, no. 6: 983–999.
- Miralles, D. G., J. Vilà-Guerau de Arellano, T. R. McVicar, and M. D. Mahecha. 2025. "Vegetation–Climate Feedbacks Across Scales." *Annals of the New York Academy of Sciences* 1544, no. 1: 27–41. <https://doi.org/10.1111/nyas.15286>.
- Monteith, J., and M. Unsworth. 2013. *Principles of Environmental Physics: Plants, Animals, and the Atmosphere*. Academic Press.
- Monteith, J. L. 1965. "Evaporation and Environment." In *Symposia of the Society for Experimental Biology*, vol. 19, 205–234. Cambridge University Press (CUP).
- Monteith, J. L. 1995. "A Reinterpretation of Stomatal Responses to Humidity." *Plant, Cell & Environment* 18, no. 4: 357–364. <https://doi.org/10.1111/j.1365-3040.1995.tb00371.x>.
- Monteith, J. L., and M. H. Unsworth. 1990. *Principles of Environmental Physics*. Vol. 1. Edward Arnold.
- Mott, K. A., and D. F. Parkhurst. 1991. "Stomatal Responses to Humidity in Air and Helox." *Plant, Cell & Environment* 14, no. 5: 509–515. <https://doi.org/10.1111/j.1365-3040.1991.tb01521.x>.
- Mukherjee, S., and A. K. Mishra. 2021. "Increase in Compound Drought and Heatwaves in a Warming World." *Geophysical Research Letters* 48, no. 1: e2020GL090617. <https://doi.org/10.1029/2020GL090617>.
- Nelson, J. A., N. Carvalhais, M. Cuntz, et al. 2018. "Coupling Water and Carbon Fluxes to Constrain Estimates of Transpiration: The TEA Algorithm." *Journal of Geophysical Research: Biogeosciences* 123, no. 12: 3617–3632. <https://doi.org/10.1029/2018JG004727>.
- Nelson, J. A., O. Pérez-Priego, S. Zhou, et al. 2020. "Ecosystem Transpiration and Evaporation: Insights From Three Water Flux Partitioning Methods Across FLUXNET Sites." *Global Change Biology* 26, no. 12: 6916–6930. <https://doi.org/10.1111/gcb.15314>.
- Nicholls, E. M., C. Spence, N. Hedstrom, J. D. Lenters, and P. D. Blanken. 2024. "Lake Superior Evaporation: A Long-Term Eddy Covariance Dataset at Stannard Rock Lighthouse (2008–2022)." *Scientific Data* 11, no. 1: 1152. <https://doi.org/10.1038/s41597-024-03940-7>.
- Novick, K. A., D. L. Ficklin, P. C. Stoy, et al. 2016. "The Increasing Importance of Atmospheric Demand for Ecosystem Water and Carbon Fluxes." *Nature Climate Change* 6, no. 11: 1023–1027. <https://doi.org/10.1038/nclimate3114>.
- Olivier, F. C., and A. Singels. 2012. "The Effect of Crop Residue Layers on Evapotranspiration, Growth and Yield of Irrigated Sugarcane." *Water SA* 38, no. 1: 77–86. <https://doi.org/10.4314/wsa.v38i1.10>.
- Olivier, F. C., and A. Singels. 2015. "Increasing Water Use Efficiency of Irrigated Sugarcane Production in South Africa Through Better Agronomic Practices." *Field Crops Research* 176: 87–98. <https://doi.org/10.1016/j.fcr.2015.02.010>.
- Oren, R. J. S. S., J. S. Sperry, G. G. Katul, et al. 1999. "Survey and Synthesis of Intra-and Interspecific Variation in Stomatal Sensitivity to Vapour Pressure Deficit." *Plant, Cell & Environment* 22, no. 12: 1515–1526. <https://doi.org/10.1046/j.1365-3040.1999.00513.x>.
- Panwar, A., M. Renner, and A. Kleidon. 2020. "Imprints of Evaporation and Vegetation Type in Diurnal Temperature Variations." *Hydrology and Earth System Sciences Discussions* 2020: 1–27. <https://doi.org/10.5194/hess-24-4923-2020>.
- Plett, D. C., K. Ranathunge, V. J. Melino, N. Kuya, Y. Uga, and H. J. Kronzucker. 2020. "The Intersection of Nitrogen Nutrition and Water Use in Plants: New Paths Toward Improved Crop Productivity." *Journal of Experimental Botany* 71, no. 15: 4452–4468. <https://doi.org/10.1093/jxb/eraa049>.
- Querejeta, J. I., I. Prieto, C. Armas, et al. 2022. "Higher Leaf Nitrogen Content Is Linked to Tighter Stomatal Regulation of Transpiration and More Efficient Water Use Across Dryland Trees." *New Phytologist* 235, no. 4: 1351–1364. <https://doi.org/10.1111/nph.18254>.
- Reichstein, M., E. Falge, D. Baldocchi, et al. 2005. "On the Separation of Net Ecosystem Exchange Into Assimilation and Ecosystem Respiration: Review and Improved Algorithm." *Global Change Biology* 11, no. 9: 1424–1439. <https://doi.org/10.1111/j.1365-2486.2005.001002.x>.
- Reyes, J. A. O., A. S. Carpentero, P. J. A. Santos, and E. F. Delfin. 2020. "Effects of Water Regime, Genotype, and Formative Stages on the Agro-Physiological Response of Sugarcane (*Saccharum officinarum* L.) to Drought." *Plants* 9, no. 5: 661. <https://doi.org/10.3390/plant9050661>.
- Richardson, A. D., and D. Y. Hollinger. 2007. "A Method to Estimate the Additional Uncertainty in Gap-Filled NEE Resulting From Long Gaps in the CO2 Flux Record." *Agricultural and Forest Meteorology* 147, no. 3–4: 199–208. <https://doi.org/10.1016/j.agrformet.2007.06.004>.
- Rotenberg, E., F. Tatarinov, J. D. Muller, and D. Yakir. 2025. "Evapotranspiration Saturation Amplifies Climate Sensitivity of Terrestrial Water Yield." *Nature Communications* 16: 11577. <https://doi.org/10.1038/s41467-025-66570-6>.
- Sabot, M. E., M. G. De Kauwe, A. J. Pitman, et al. 2022. "One Stomatal Model to Rule Them All? Toward Improved Representation of Carbon and Water Exchange in Global Models." *Journal of Advances in Modeling Earth Systems* 14, no. 4: e2021MS002761. <https://doi.org/10.1029/2021MS002761>.

- Santos, L. C., R. D. Coelho, F. S. Barbosa, et al. 2019. "Influence of Deficit Irrigation on Accumulation and Partitioning of Sugarcane Biomass Under Drip Irrigation in Commercial Varieties." *Agricultural Water Management* 221: 322–333. <https://doi.org/10.1016/j.agwat.2019.05.013>.
- Schumann, K., B. Schuldt, M. Fischer, C. Ammer, and C. Leuschner. 2024. "Xylem Safety in Relation to the Stringency of Plant Water Potential Regulation of European Beech, Norway Spruce, and Douglas-Fir Trees During Severe Drought." *Trees* 38, no. 3: 607–623. <https://doi.org/10.1007/s00468-024-02499-5>.
- Singh, Y., R. L. Choudhary, A. Chaudhary, N. More, and N. P. Singh. 2021. "Impact of Conservation Agriculture and Residue Management on Soil Properties Under Sugarcane-Based Cropping Systems." In *Conservation Agriculture: A Sustainable Approach for Soil Health and Food Security: Conservation Agriculture for Sustainable Agriculture*, 239–266. Springer Singapore. https://doi.org/10.1007/978-981-16-0827-8_11.
- Singta, S., A. Chidthaisong, D. Komori, V. Surapioith, and W. Kim. 2018. "Estimation of Evapotranspiration From Sugarcane Plantation Using Eddy Covariance Method." *Journal of Sustainable Energy & Environment* 9: 1–9.
- Stoy, P. C., T. S. El-Madany, J. B. Fisher, et al. 2019. "Reviews and Syntheses: Turning the Challenges of Partitioning Ecosystem Evaporation and Transpiration Into Opportunities." *Biogeosciences* 16, no. 19: 3747–3775. <https://doi.org/10.5194/bg-16-3747-2019>.
- Sun, H., M. Lu, Y. Yang, et al. 2023. "Revisiting the Role of Transpiration in the Variation of Ecosystem Water Use Efficiency in China." *Agricultural and Forest Meteorology* 332: 109344. <https://doi.org/10.1016/j.agrformet.2023.109344>.
- Sutherlin, C. E., N. A. Brunzell, G. de Oliveira, T. E. Crews, L. R. DeHaan, and G. Vico. 2019. "Contrasting Physiological and Environmental Controls of Evapotranspiration Over Kernza Perennial Crop, Annual Crops, and C4 and Mixed C3/C4 Grasslands." *Sustainability* 11, no. 6: 1640. <https://doi.org/10.3390/su11061640>.
- Swain, H. M., E. H. Boughton, P. J. Bohlen, and L. O. G. Lollis. 2013. "Trade-Offs Among Ecosystem Services and Disservices on a Florida Ranch." *Rangelands* 35, no. 5: 75–87. <https://doi.org/10.2111/RANGE LANDS-D-13-00053.1>.
- Takaragawa, H., Y. Terajima, and K. Okamoto. 2025. "Improvement in the Intrinsic Water Use Efficiency of Sugarcane by Intergeneric Hybridization With *Erianthus Arundinaceus*." *Frontiers in Plant Science* 16: 1649112. <https://doi.org/10.3389/fpls.2025.1649112>.
- Tejera, M., N. N. Boersma, S. V. Archontoulis, F. E. Miguez, A. VanLoocke, and E. A. Heaton. 2022. "Photosynthetic Decline in Aging Perennial Grass Is Not Fully Explained by Leaf Nitrogen." *Journal of Experimental Botany* 73, no. 22: 7582–7595. <https://doi.org/10.1093/jxb/erac382>.
- Thornton, P. E., M. M. Thornton, B. W. Mayer, et al. 2016. *Daymet: Daily Surface Weather Data on a 1-Km Grid for North America, Version 3*. ORNL DAAC.
- Tippayawat, A., S. Jogloy, N. Vorasoot, et al. 2023. "Differential Physiological Responses to Different Drought Durations Among a Diverse Set of Sugarcane Genotypes." *Agronomy* 13, no. 10: 2594. <https://doi.org/10.3390/agronomy13102594>.
- Tripathy, K. P., S. Mukherjee, A. K. Mishra, M. E. Mann, and A. P. Williams. 2023. "Climate Change Will Accelerate the High-End Risk of Compound Drought and Heatwave Events." *Proceedings of the National Academy of Sciences of the United States of America* 120, no. 28: e2219825120. <https://doi.org/10.1073/pnas.2219825120>.
- USDA. 2021. "National Agricultural Statistics Service Homepage." <https://www.nass.usda.gov/>.
- Vargas Zeppetello, L. R., K. A. McColl, J. A. Bernau, et al. 2023. "Apparent Surface Conductance Sensitivity to Vapour Pressure Deficit in the Absence of Plants." *Nature Water* 1, no. 11: 941–951. <https://doi.org/10.1038/s44221-023-00147-9>.
- Wagle, P., V. G. Kakani, and R. L. Huhnke. 2016. "Evapotranspiration and Ecosystem Water Use Efficiency of Switchgrass and High Biomass Sorghum." *Agronomy Journal* 108, no. 3: 1007–1019. <https://doi.org/10.2134/agronj2015.0149>.
- Wagle, P., X. Xiao, T. E. Kolb, et al. 2016. "Differential Responses of Carbon and Water Vapor Fluxes to Climate Among Evergreen Needleleaf Forests in the USA." *Ecological Processes* 5, no. 1: 8. <https://doi.org/10.1186/s13717-016-0053-5>.
- Wang, C., S. Wu, M. Tankari, et al. 2018. "Stomatal Aperture Rather Than Nitrogen Nutrition Determined Water Use Efficiency of Tomato Plants Under Nitrogen Fertigation." *Agricultural Water Management* 209: 94–101. <https://doi.org/10.1016/j.agwat.2018.07.020>.
- Wang, H. J., W. J. Riley, and W. D. Collins. 2015. "Statistical Uncertainty of Eddy Covariance CO₂ Fluxes Inferred Using a Residual Bootstrap Approach." *Agricultural and Forest Meteorology* 206: 163–171. <https://doi.org/10.1016/j.agrformet.2015.03.011>.
- Whitehead, D. 1998. "Regulation of Stomatal Conductance and Transpiration in Forest Canopies." *Tree Physiology* 18, no. 8–9: 633–644. <https://doi.org/10.1093/treephys/18.8.9.633>.
- Xu, M., Q. Wang, F. Yang, et al. 2022. "The Responses of Photosynthetic Light Response Parameters to Temperature Among Different Seasons in a Coniferous Plantation of Subtropical China." *Ecological Indicators* 145: 109595. <https://doi.org/10.1016/j.ecolind.2022.109595>.
- Yang, S., J. Zhang, J. Han, et al. 2025. "The Ratio of Transpiration to Evapotranspiration Dominates Ecosystem Water Use Efficiency Response to Drought." *Agricultural and Forest Meteorology* 363: 110423. <https://doi.org/10.1016/j.agrformet.2025.110423>.
- Yimam, Y. T., T. E. Ochsner, and G. A. Fox. 2017. "Hydrologic Cost-Effectiveness Ratio Favors Switchgrass Production on Marginal Croplands Over Existing Grasslands." *PLoS One* 12, no. 8: e0181924. <https://doi.org/10.1371/journal.pone.0181924>.
- Zeri, M., M. Z. Hussain, K. J. Anderson-Teixeira, E. DeLucia, and C. J. Bernacchi. 2013. "Water Use Efficiency of Perennial and Annual Bioenergy Crops in Central Illinois." *Journal of Geophysical Research: Biogeosciences* 118, no. 2: 581–589. <https://doi.org/10.1002/jgrg.20052>.
- Zhang, Q., D. L. Ficklin, S. Manzoni, et al. 2019. "Response of Ecosystem Intrinsic Water Use Efficiency and Gross Primary Productivity to Rising Vapor Pressure Deficit." *Environmental Research Letters* 14, no. 7: 074023. <https://doi.org/10.1088/1748-9326/ab2603>.

Supporting Information

Additional supporting information can be found online in the Supporting Information section. **Table S1:** Agronomic management for the sugarcane field (Gomez-Casanovas et al. 2024). **Table S2:** Stomatal model performance parameters estimated for Unified Stomatal Optimization (USO) and Oren models for sugarcane (cane), improved pasture (IMP), and semi-native pasture (SN) over the study periods. For the USO model, Akaike information criterion (AIC) and root mean square error (RMSE) are shown, and for the Oren model, the coefficient of determination (R^2) is shown. **Table S3:** Sensitivity of the TEA model to changes in prediction percentile (Q55, Q65, Q75, Q85, and Q95), CSWI limit (0, −0.25, −0.5, −0.75, and −1 mm), number of trees (80, 85, 90, 95, and 100), and random seed (11, 22, 33, 44, and 55) used during model training. **Figure S1:** Seasonal variation in (A) air temperature and (B) daily precipitation in 2019, 2020, 2021, and 2022. **Figure S2:** Evapotranspiration partitioning to evaporation (non-productive water loss) and transpiration (productive water use) using Transpiration Estimation Algorithm (TEA) for (A) sugarcane (Cane), (B) improved pasture (IMP), and (C) semi-native pasture (SN) across the study period. From 2/6/2019 to 2/16/2020 was defined as cane crop from planting until first harvest (i.e., plant cane; PC), from 2/17/2020 to 2/8/2021 as cane crop from first to second harvest (i.e., first ratoon cane; FRC), and from 2/9/2021 to 4/6/2022 as

cane crop from second to third harvest (i.e., second ratoon cane; SRC). **Figure S3:** Average of aerodynamic conductance (g_a) (A) and g_a for sugarcane (Cane), improved pasture (IMP), and semi-native pasture (SN) (B) in 2019, 2020, 2021, and 2022. PC was defined as sugarcane crop from planting until first harvest (here, from 2/6/2019 to 2/16/2020), FRC as cane crop from first to second harvest (here, from 2/17/2020 to 2/8/2021), and SRC as cane crop from second to third harvest (here, from 2/9/2021 to 4/6/2022). **Figure S4:** Relationship between stomatal conductance (g_s) and vapor pressure deficit (VPD) across three land uses. Each circle represents average g_s within discrete VPD bins, with each bin spanning 0.2 kPa across the study period. The shaded ribbons represent the 95% confidence interval. Across land uses, g_s varied with average VPD range during the study period following the VPD-response framework recommended by Novick et al. (2016).