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Evapotranspiration Partitioning Using Flux Tower Data in a Semi-Arid Ecosystem

Kanak Kanti Kar[1] | Ryan Haggerty[1] | Harmandeep Sharma[2] | Dipankar Dwivedi[3] | Tirthankar Roy[1]

[1]Department of Civil and Environmental Engineering, University of Nebraska-Lincoln, Omaha, Nebraska, USA | [2]Department of Natural Resources and Environmental Design, North Carolina A&T State University, Greensboro, North Carolina, USA | [3]Climate and Ecosystem Sciences Division, Lawrence Berkeley National Laboratory, Berkeley, California, USA

Correspondence: Tirthankar Roy (roy@unl.edu)

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ABSTRACT

Information about evapotranspiration (ET) and its components, that is, evaporation and transpiration, is crucial for a wide range of water and ecosystem management applications. However, partitioning ET into its two components is often challenging because of their spatiotemporal variabilities and lack of process understanding. This study developed a machine learning (ML) framework to shed light on ET processes and assess the relative importance of different drivers by incorporating hydrometeorology and biomass productivity variables. The Shapley Additive Explanations (SHAP) approach was applied to enhance explainability and rank the importance of ET drivers and their components. A total of 62 variables covering hydrometeorological and biomass productivity dimensions were considered from the Reynolds Creek Critical Zone Observatory (CZO) station in Idaho. The variable importance assessment identified the leading drivers individually for evaporation, transpiration and ET (soil water content for evaporation, vapour pressure deficit for transpiration and soil water content for ET). The results further highlighted the value of combining hydrometeorological and biomass productivity variables to achieve better predictability of ET processes.

1 | Introduction

Evapotranspiration (ET) is one of the vital components of the water cycle, describing the movement of water from soil and plants into the atmosphere (Prein and Pendergrass 2019; Koutsoyiannis 2020; He et al. 2021; Raimi et al. 2021; Yang, Yang et al. 2021). ET consists of evaporation, a physical process of liquid water vaporising and transpiration, the loss of water vapour through plant stomata. Understanding ET-related mechanisms and the partitioned components of ET, that is, evaporation and transpiration, is essential for a wide range of water and ecosystem management applications, such as irrigation scheduling, sustainable water usage, water conservation and ecological preservation (Huang et al. 2019; Ma and Song 2019; Srivastava et al. 2024).

Significant efforts have been made to advance the scientific understanding of ET partitioning. Some of the well-known methods for this purpose include isotope measurement (Kool et al. 2014), carbon–water vapour correlation (Scanlon and Sahu 2008), numerical models like Shuttleworth-Wallace (Zhou et al. 2006) and software models, such as Hydrus-1D (Tafteh and Sepaskhah 2012); however, they have their limitations. These methods often rely on data, such as water use efficiency, which is seldom available on a wide scale or requires extensive instrumentation. For example, isotope measurement techniques are instrumentation-heavy and often impractical for large-scale or routine applications. Similarly, carbon–water vapour correlation methods, also popular for ET partitioning, depend on continuous and precise measurements of carbon fluxes—something that is not always readily available. While powerful, numerical models and software like Hydrus-1D often require detailed input data on soil properties and climatic variables that may not be readily accessible or unavailable for many areas. This is where machine learning (ML) can play a crucial role. ML algorithms can efficiently mine valuable information from the available data and facilitate scientific understanding of the ET partitioning process with high accuracy and much reduced computational costs.

ML has already been effectively applied to various environmental and hydrological problems, such as obtaining high-accuracy leaf area index (LAI) data (Gao et al. 2021, 2023) and correcting relative humidity data (Zhang et al. 2023). ML has also been used for ET estimation (Whitley et al. 2009; Dou and Yang 2018; Kazemi et al. 2020; Liu et al. 2020; Gao et al. 2021, 2023; Chen et al. 2023); however, ET partitioning remains largely unexplored in this context. Furthermore, most studies aimed for high accuracy but often neglected insights into the drivers behind ET (Eichelmann et al. 2022; Stapleton et al. 2022). For example, Eichelmann et al. (2022) developed an artificial neural network model that provides high accuracy but limited knowledge of the relative importance of different variables. Similarly, Stapleton et al. (2022) used recursive feature elimination to improve model performance; however, the underlying processes of ET partitioning were not thoroughly explored.

These limitations necessitate delving into the potential of the ML methods for accurately partitioning ET into its components. Therefore, this study aims to improve the accuracy of ET partitioning and the understanding of its drivers. We hypothesize that integrating hydrometeorological and biomass productivity variables into an ML framework provides a robust approach for accurately estimating ET and its components and identifying their relevant drivers. Our approach utilises the random forest (RF) algorithm to test our hypothesis. By integrating this algorithm with hydrometeorological and biomass productivity variables, our study aims to accurately estimate evaporation, transpiration and ET individually, followed by variable importance assessment to understand the role of different drivers by implementing an explainable AI technique, Shapley Additive Explanations (SHAP).

2 | Data and Methods

2.1 | Study Area and Data

The experimental study site is the Reynolds Creek Critical Zone Observatory (CZO) (Seyfried et al. 2018), located in the Owyhee Mountains of southwestern Idaho, USA (latitude 43.1675° N, longitude 116.7132° W, elevation 1425 m). This semi-arid site is situated is notable for its critical ecosystem and biodiversity. The USDA-ARS Northwest Watershed Research Center operates the site (AmeriFlux ID: US-Rws, Reynolds Creek Wyoming big sagebrush) and all data (hydrometeorology and biomass productivity) were collected using the reliable Eddy Covariance (EC) method. The geographical location of the study site is shown in Figure 1, where Reynolds Creek drains north of the Snake River. The dominant vegetation is Wyoming sagebrush (*Artemisia tridentata* ssp. *wyomingensis*). Although the area is classified as a cold desert, the climate varies, ranging from semi-arid to subhumid. Precipitation dominates at lower elevations, while snowfall is more common at higher elevations (Sharma, Reinhardt et al. 2020). The annual average air temperature (TA) ranges from 4.9°C to 8.9°C, and the mean yearly precipitation varies from 230 to 1100 mm, and snowfall accounts for 20%–70%, depending on elevation (Sharma, Reinhardt et al. 2020).

The US-Rws dataset is available through the AmeriFlux data-sharing platform under an open-source licence (https://ameriflux.lbl.gov/sites/site-search/). The study covers approximately 7 years of data (2014–2020), considering 62 variables, including TA, shortwave and longwave radiation (SW and LW), vapour pressure deficit (VPD), atmospheric pressure (PA), precipitation

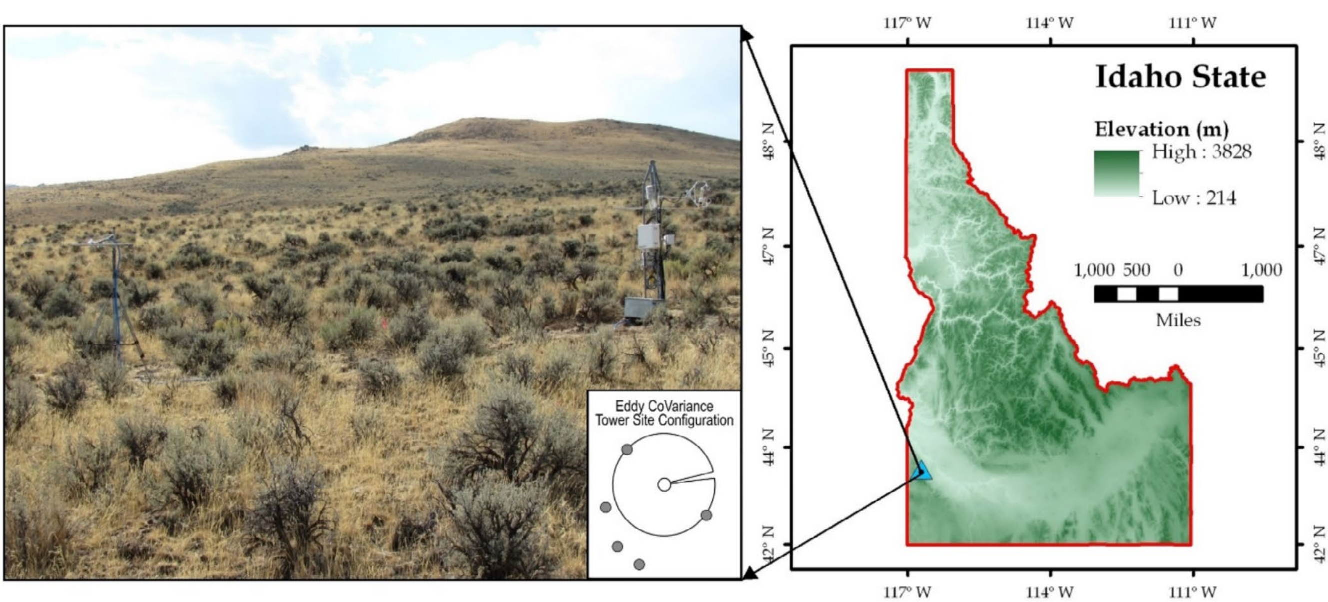

FIGURE 1 | Study location at Reynolds Creek, Idaho, USA. The station location photo was taken from the Critical Zone Collaborative Network website (https://czo-archive.criticalzone.org/reynolds/) and the EC flux tower.

(P), wind speed (WS), soil conditions (e.g., temperature, water content) and biomass productivity as indicated by net ecosystem exchange (NEE), ecosystem respiration (RECO) and gross primary production (GPP). Subscripts attached to acronyms indicate their derivation methods and numerical subscripts specify the depth for depth-dependent variables (detailed descriptions are available in Table S1). We obtained the daily raw data set from the EC system covering the period from 1 January 2014, to 31 December 2020, which spans 2556 days. Additionally, we collected observed sap flow (transpiration) data from 15 May 2015, to 20 October 2017, covering 889 days and applied it for ML (training and testing). From 2015 to 2017, we selected predictor variables for the corresponding time series and found that 5.17% of the data was missing (Tables S2–S4). Daily interval data was used, and rows with missing values were discarded before running the ML algorithm. Biomass productivity variables (NEE, GPP and RECO) were not used to estimate/gap-fill the target ET from flux tower latent heat flux observations, ensuring no potential confounders. Missing values were filled using marginal distribution sampling and model efficiency analysis (Josse et al. 2024; Thurow et al. 2024).

Several assumptions were employed to simplify the challenge of establishing ground-truth data for the contributions of evaporation, transpiration and ET to the hydrological cycle, drawing on insights from Fellows et al. (2017) and Flerchinger et al. (2020), who offer valuable data on carbon and water fluxes within the Reynolds CZO, particularly, in a sagebrush ecosystem (Fellows et al. 2017; Flerchinger et al. 2020). For example, Fellows et al. (2017) offer a comprehensive dataset on partitioned carbon and energy fluxes, noting potential sensor heating issues with the LI7500A, which may affect data accuracy during cooler weather. Flerchinger et al. (2020) analyse water and carbon fluxes across an elevational gradient, highlighting significant differences in GPP with elevation. Both studies are based on accurate sensor calibration and data interpretation to understand the ecosystem dynamics and hydrometeorological impacts. Our framework considers a well-suited ML model to reduce the complexity of measuring ET and its components. Our target variables were ET, evaporation and transpiration, where ET was calculated from latent heat flux (source: Ameriflux) and transpiration was estimated from sap flux data (https://scholarworks.boisestate.edu/reynoldscreek/15/). Our study calculated ET (mm/day) from the latent heat flux (W/m^2), using standard conversion methods. ET (mm/day) was computed by dividing the latent heat flux (W/m^2) by the latent heat of vaporisation (J/kg) and the density of water (kg/m^3). However, our model did not use the latent heat flux from the EC data set as a predictor variable. While we acknowledge that the EC tower's footprint may vary in time and space, the measurements were considered representative of the overall study area, given the dominance of sagebrush in the region. Sap flow data were used to estimate transpiration, as they capture the entire plant's water uptake. While external losses or storage effects could introduce variability, these measurements represent the site's overall conditions. Sap flux stations were positioned within a 50–70 m radius of the EC tower, corresponding to the range of flux footprints (Seyfried et al. 2018; Chu et al. 2021).

Although the precise footprint area was not calculated, we assume that the sensors capture most of the transpiration, as sagebrush is the dominant plant species in the region. Sap flux values were reported per unit leaf area of the shrub (Sharma, Reinhardt et al. 2020). Sap flux measurements are recorded continuously at 15-, 30-min or hourly intervals, allowing precise synchronisation with the EC data for more accurate comparison and analysis. We used sap flux sensors to measure transpiration. They directly capture plant water use, making them ideal for tracking dynamics in sagebrush. Other methods, like lysimeters or soil moisture balance, were impractical due to the large area and focus on plant-level uptake. Sap flux data complement the EC measurements of ET. We multiplied these values by the LAI of Wyoming shrub species at the study site to report sap flux per unit ground area (Renwick et al. 2019). Since the study site is dominated by mainly Wyoming big sagebrush (*Artemisia tridentata* ssp. *wyomingensis*) and greasewood (*Sarcobatus* Nees), we anticipate relatively low uncertainties in transpiration estimations. Once the input and variable data were collected, they were cleaned, outliers were removed and the data were transformed into a format the modelling algorithm could use.

2.2 | Methods

2.2.1 | RF Model

RF is an ML algorithm based on an ensemble of decision trees (Breiman et al. 2017). In this case, multiple decision trees are used to form a forest, where increasing the number of trees reduces the variance and generalisation error. This study used hydrometeorological and biomass productivity variables to develop RF models separately for evaporation, transpiration and ET. While setting up the model, we used six for the maximum depth and 10 for the number of trees in the forest.

The data set was not randomly split into training and testing sets. Instead, we used a sequential approach, where the first 80% of the time series data was selected as the training, and the remaining 20% was used for testing. We used the RF implementation from the scikit-learn Python package, a widely recognised ML tool known for its accuracy and ability to handle datasets with many predictor variables. This ML package is well-documented, extensively tested and has been used in various prediction studies (e.g., Kühnlein et al. 2014; Li et al. 2016; Schoppa et al. 2020, Mital et al. 2020; Dwivedi et al. 2022).

2.2.2 | SHAP

We implemented an explainable AI method called the SHAP to robustly understand the importance of different evaporation, transpiration and ET drivers. SHAP helped us understand the contributions of hydrometeorology and biomass productivity variables, individually and in combination, in predicting evaporation, transpiration and ET. The Shapely value represents the average change in the model prediction when a feature is added to various feature sets, weighted by the number of feature sets. It assigns the importance value to each input feature for a given prediction. Therefore, the SHAP value represents the mean marginal influence of each variable on the model prediction across all possible combinations of features, considering their interactions (Yang, Chen et al. 2021). One of the advantages of SHAP is its ability to reveal a feature's positive and negative effects in each instance (Ullah et al. 2023). A SHAP value of zero indicates no contribution of the given feature to the prediction, while positive and negative values refer to increased and decreased predictions, respectively (Lundberg and Lee 2017; Lundberg et al. 2018). The larger a variable's mean absolute SHAP value, the more influential it is in the lot.

2.2.3 | Framework for ET Partitioning

To partition ET into evaporation and transpiration and link them with their drivers and components, we considered three scenarios: hydrometeorology, biomass productivity and a combination of both. In this study, ET was derived from the latent heat flux of EC data, while transpiration was measured and upscaled from sap flow. After that, transpiration was subtracted from ET to get the evaporation. The proposed framework, illustrated in Figure 2, involves several steps and applies each scenario to our study site in the Reynolds Creek CZO. It begins with initial dataset preparation and specification of the target variable, followed by RF regression analysis and feature selection using SHAP. The methodology concludes with model training, model performance evaluation (KGE score), and variable importance analysis.

3 | Results and Discussion

3.1 | Model Performance Evaluation

With the newly developed ML-based ET partitioning framework, we evaluated the model performance using the Kling-Gupta Efficiency (KGE) scores (Gupta et al. 2009) score (Table 1). KGE scores interpret how well a model predicts observed data, whereas values closer to 1 indicate better performance and values closer to $-\infty$ indicate poor performance. The RF model achieved a KGE score of 0.679 when utilising only hydrometeorological variables for evaporation and 0.568 when using only biomass productivity variables, indicating moderate predictive accuracy in both cases. In other words, the model was more effective in predicting evaporation within the hydrometeorological context. The combination of hydrometeorological and biomass productivity variables further improved the evaporation prediction, yielding a KGE score of 0.783.

The model demonstrated a KGE of 0.614 for transpiration for hydrometeorology, while biomass productivity alone indicated poor performance (0.277). The transpiration data could introduce variability, as it relies on upscaling sap flux measurements, which might not comprehensively capture site-wide dynamics. However, combining hydrometeorological and biomass productivity variables provided a better context for predicting transpiration, resulting in a KGE score 0.626. The biomass productivity variables may not exhibit strong direct correlations with transpiration at the temporal resolution of this analysis. Transpiration has a complex dependence on multiple interacting factors, including soil moisture, VPD and plant physiological traits, which were not fully encapsulated by the biomass productivity data set. ET showed a higher KGE score than evaporation or transpiration individually, with the combined category achieving the highest KGE (0.865). In contrast, the KGE scores for hydrometeorology and biomass productivity alone were 0.855 and 0.781, respectively.

We explored the correlation between predictors and target variables to understand better the relationships driving the model's performance (evaporation, transpiration and ET). Our correlation plots (Figure S1) show strong linear relationships between certain predictors, such as soil water content, WS, friction velocity, GPP, RECO, incoming SW and the target variables, supporting our ML analysis. While correlation analysis identifies linear

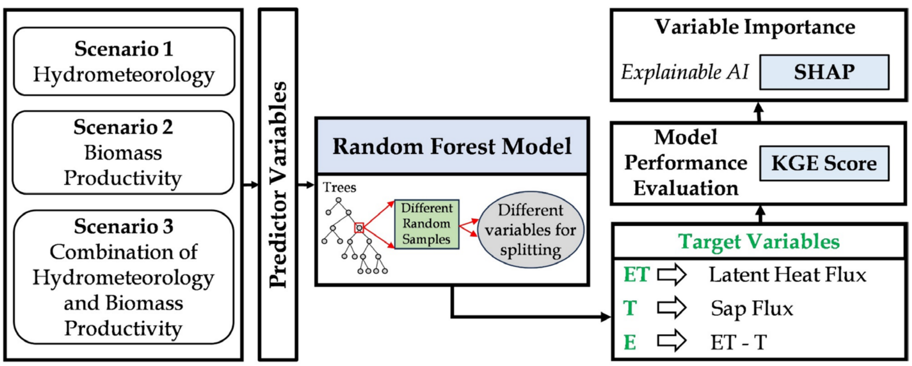

FIGURE 2 | Methodological framework to predict ET and its components (evaporation and transpiration).

TABLE 1 | Model performance evaluation by KGE score.

Components	Hydrometeorology	Biomass productivity	Combined (hydrometeorology + biomass productivity)
Evaporation	0.679	0.568	0.783
Transpiration	0.614	0.277	0.626
ET	0.855	0.781	0.865

relationships, RFs capture linear and nonlinear interactions. The ML approach we employed was highly effective. Even predictors with weaker or mixed correlations were effectively modelled (e.g., NEE relationship with evaporation, transpiration and ET), as evidenced by the model's strong performance. This success suggests that our approach can capture both the linear relationships and more intricate nonlinear dynamics in the data.

The results indicate that hydrometeorological factors are crucial in predicting ET, evaporation and transpiration compared to biomass productivity alone. Integrating both variable types within an ML model improves prediction accuracy between observed and simulated datas ets. Thus, the combined approach to ET is more robust (KGE: 0.865) than predictions based solely on individual components (evaporation and transpiration).

3.2 | Variable Importance by SHAP Analysis

3.2.1 | Hydrometeorological Effects on Evaporation, Transpiration and ET

Figure 3 illustrates the impact of hydrometeorological variables on ET, transpiration and evaporation using mean absolute SHAP value analysis. The analysis identifies shallow soil water content (SHAP value: 0.49) as the primary driver of evaporation. While higher moisture supports surface evaporation, drier soils can paradoxically increase evaporation due to elevated VPD and amplified temperature gradients, which enhance heat transfer and evaporation (Lu et al. 2005; Alessi et al. 2022). Reduced moisture also raises sensible heat flux, further intensifying evaporation (Cioni and Hohenegger 2017). Friction velocity (SHAP value: 0.06) contributes by increasing turbulence near the soil, aiding in water vapour removal, while soil desiccation cracking creates new surfaces for evaporation (Zhou et al. 2006). As soil moisture decreases, its ability to retain water declines in semi-arid regions, resulting in greater surface evaporation (Vautard et al. 2007; DuPre et al. 2022). These dynamics are, particularly, relevant for agriculture since effective soil moisture management leads to reduced water loss and stable crop yields (Daryanto et al. 2016; Dai et al. 2022). In summary, evaporation is driven by the interactions of temperature gradients, shallow soil water content, friction velocity and soil structure, emphasising the need for careful moisture management in the face of climate change.

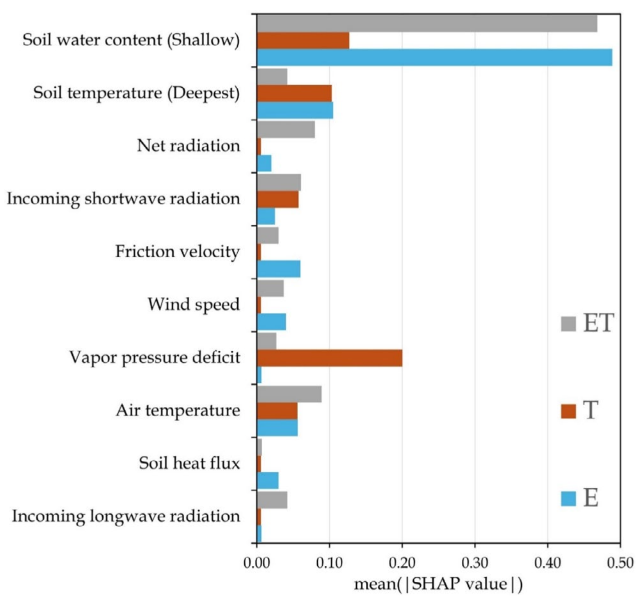

FIGURE 3 | Hydrometeorological variables impact on evaporation, transpiration and ET.

VPD (SHAP value: 0.2) is the primary driver for transpiration, with higher VPD increasing atmospheric dryness and water loss from plant leaves (Oren et al. 1996). Shallow soil water content (SHAP value: 0.13) ensures root-zone moisture and, when reduced, limits water uptake, decreasing transpiration (Naithani et al. 2012). Soil temperature (SHAP value: 0.10) raises plant water demands, while SW (SHAP value: 0.06) provides energy for photosynthesis, increasing water loss through transpiration (Boote et al. 2018).

ET, which combines evaporation and transpiration, is essential for managing water resources and agriculture. Our analysis shows that shallow soil water content is the most significant factor for evaporation (SHAP value: 0.47), while friction velocity (SHAP value: 0.03) and net radiation (SHAP value: 0.08) play secondary roles. VPD mainly influences transpiration with a SHAP value of 0.2, negligible in ET (SHAP value: 0.03). These relationships show that ET is enormously complex in its relationship with hydrometeorological factors, representing the importance of a better understanding these different dynamics for integrated water resources management.

3.2.2 | Biomass Productivity Effects on Evaporation, Transpiration and ET

Based on SHAP values (Figure 4), gross primary productivity (GPP) is a key driver for both evaporation and transpiration, with SHAP values of 0.25 for evaporation and 0.17 for transpiration. For ET, GPP has the highest influence (SHAP value: 0.33), followed closely by RECO with a SHAP value of 0.28. RECO also significantly influences transpiration (SHAP value: 0.11) by influencing air movement and water vapour exchange around leaves. The common environmental factors impacting all three processes—evaporation, transpiration and ET—include temperature, soil moisture and VPD. These factors affect the partitioning of GPP and RECO between evaporation and

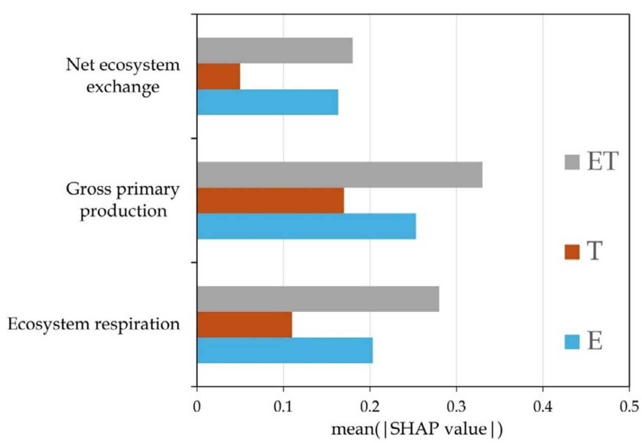

FIGURE 4 | Biomass productivity variables impact on evaporation, transpiration and ET.

transpiration, making their influence strongly interdependent under varying conditions. Higher temperatures and drier conditions enhance evaporation and transpiration, while higher humidity can limit evaporation by reducing the vapour pressure gradient (Abeshu et al. 2024; Michel et al. 2024).

GPP influences evaporation through its effect on water availability and transpiration. However, this impact is shaped by environmental factors such as temperature and VPD, which drive both GPP and ET (Abeshu et al. 2024; Michel et al. 2024). Biomass in the canopy reduces turbulence, stabilising the microclimate and limiting moisture transport, which impacts evaporation (Bonan et al. 2018; Chen et al. 2019). Excessive turbulence can reduce moisture transport efficiency, so canopy structure plays a crucial role (Chen et al. 2020). GPP-driven transpiration can increase evaporation in dry conditions, while in humid conditions, it may reduce evaporation by lowering the vapour pressure gradient. While GPP does not directly alter turbulence, the changes in transpiration and local humidity indirectly affect evaporation by modifying the vapour pressure gradient, which influences the efficiency of turbulent transport (Chowdhuri et al. 2022).

GPP is the most influential factor for transpiration, controlling stomatal activity, which regulates CO_2 and water vapour exchange (Chowdhuri et al. 2022). Elevated GPP increases transpiration, limiting evaporation by reducing the vapour pressure gradient, but under drier conditions, GPP can enhance evaporation by driving higher transpiration. RECO influences transpiration by modulating air movement and water vapour exchange, with its impact strongly tied to soil moisture and temperature (Fu et al. 2022). Elevated RECO, indicating higher metabolic activity, leads to increased transpiration, which can indirectly boost evaporation through greater water vapour release, though local environmental conditions modulate this effect (Rezende et al. 2022). RECO's influence on evaporation may also involve changes in the vapour pressure gradient, as increased metabolic activity leads to greater water vapour release, potentially affecting the balance between the surface and atmosphere (dos et al. 2021).

For ET, GPP has the highest SHAP value, with RECO and NEE also contributing. Including both evaporation and transpiration in the ET model highlights their combined influence. Research on water use efficiency supports this connection between GPP, ET and the water–carbon cycle (Umair et al. 2020; Jiang et al. 2021). Temperature sensitivity in the EC measurements from FluxNet further affects the partitioning of evaporation and transpiration, complicating the interpretation due to the covariance between GPP and RECO (Yan et al. 2020; Wang et al. 2023). The strong covariance between GPP and RECO, particularly in daytime data, is likely due to their shared dependency on temperature. This interdependence affects SHAP values, as GPP and RECO often rise under favourable conditions and reflect shared environmental factors rather than independent contributions (Watanabe et al. 2021). Partitioning GPP and RECO from NEE requires precise modelling based on EC measurements, which are influenced by temperature and soil moisture, complicating the process (Endsley et al. 2022). Despite those dependencies, it can be challenging to distinguish the effect while similar variables like temperature influence both.

Overall, the different components of the climate, such as temperature and soil moisture, contribute to the interaction between RECO and evaporation, which influences the VPD by the difference between leaves and the surrounding air. This deficit increases parallel with RECO in arid conditions that accelerate water vapour escape and impact evaporation (dos et al. 2021). Elevated RECO correlates with higher metabolic activity, increasing transpiration and indirectly boosting evaporation through water vapour release. However, the vapour pressure gradient may decrease in high transpiration and humidity conditions, limiting further evaporation. Understanding how GPP and RECO are partitioned is essential for clarifying their roles in ET and improving ecosystem carbon dynamics models.

3.2.3 | Combined Hydrometeorology and Biomass Productivity Effects on Evaporation, Transpiration and ET

As illustrated in Figure 5, SHAP analysis shows that shallow SWC is the most critical factor affecting evaporation and ET, with SHAP values of 0.29 for ET and 0.35 for evaporation. SWC and VPD significantly affect transpiration with a SHAP value of 0.12 and 0.11, respectively, because they control moisture gradients and exist between the leaf and surrounding air. RECO indicates an essential role for ET and transpiration (SHAP value: 0.28 and 0.11). Friction velocity contributes to evaporation by enhancing turbulent air mixing (SHAP value: 0.04), while net radiation plays a minor role in ET (SHAP value: 0.07) and has a negligible impact on transpiration.

Higher evaporation rates are related to shallow SWC, which is linked to moisture redistribution through hydraulic processes. Water is moved from deeper soil layers to the surface through hydraulic redistributions, which increases the amount of moisture available for evaporation. As mentioned earlier, an increased SWC correlates with higher evaporation rates, providing the

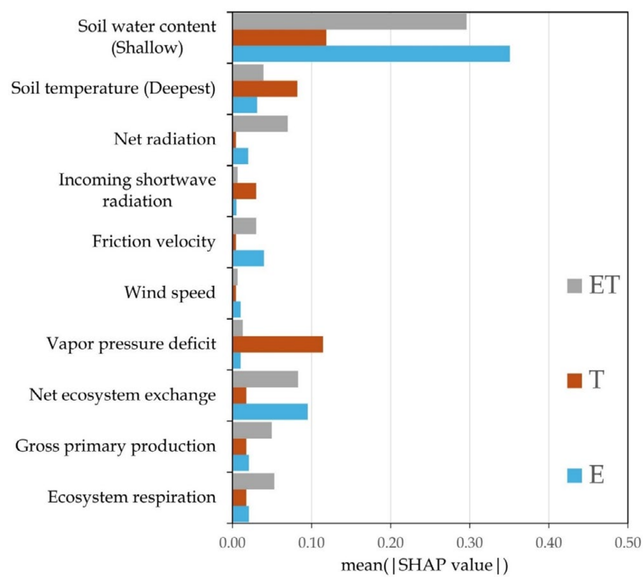

FIGURE 5 | Combined (hydrometeorology and biomass productivity) variables impact on evaporation, transpiration and ET.

moisture required for surface evaporation (Scholz et al. 2002; Or et al. 2013). Additionally, friction velocity accelerates the removal of water vapour and elevates evaporation rates by increasing air mixing near the surface (Katul and Liu 2017). With a SHAP value of 0.10 for evaporation, NEE influences plant physiology and microclimatic conditions, thus impacting evaporation. NEE represents the balance of CO_2 exchange between the ecosystem and the atmosphere (regulating photosynthesis and transpiration), thereby influencing water loss through evaporation (Jiang et al. 2012; Samuels-Crow et al. 2020).

Hydrometeorological factors, such as VPD, deepest soil temperature and SWC, are key drivers of both evaporation and transpiration. At the same time, biomass productivity plays a secondary role. As mentioned earlier, VPD is, particularly, influential as it determines the moisture gradient between leaves and surrounding air. Higher deficits typically result in increased transpiration as plants release more water vapour to balance this moisture difference (Zhao and Ji 2016; Broughton and Conaty 2022). Soil temperature (deepest) also affects transpiration by regulating root zone temperature and moisture availability, which impacts water uptake and subsequent water loss through transpiration (Zhang and Davies 1989; Gong et al. 2007).

Additionally, while friction velocity plays a key role in evaporation by driving turbulent air mixing, its influence on transpiration appears less significant. This may be due to the stronger impact of VPD and stomatal regulation on transpiration, which directly controls water vapour exchange between the leaf surface and the atmosphere. Unlike evaporation, where surface processes and turbulence are critical, transpiration is primarily regulated by internal plant mechanisms that respond to environmental conditions such as VPD and soil moisture.

While net radiation contributes to ET, its impact on transpiration is minimal, suggesting that factors like VPD and soil temperature (deepest) exert more influence on transpiration without significantly affecting ET (Zhang et al. 2015; Chen et al. 2022). As mentioned earlier, RECO impacts transpiration by altering air movement around leaves and changing CO_2 concentrations in the canopy, modulating stomatal behaviour and water loss (Bonan et al. 2014; Schymanski et al. 2015; Cawse-Nicholson et al. 2018). Our results show biomass productivity contributes significantly to ET but is a secondary component for evaporation and transpiration, revealing how these processes are interdependent in the ecosystem (Impa et al. 2005; Vaughn et al. 2016).

In summary, the complex interactions between shallow SWC, hydrometeorological factors and biomass productivity are key to fully understanding the dynamics of evaporation, transpiration and ET across ecosystems.

3.3 | Combined Interaction of Most Influential Variables on ET and Its Components

Our SHAP analysis, as illustrated in Figure 6, highlights the distribution of combined hydrometeorological and biomass productivity impacts on ET, evaporation and transpiration. Each dot represents a single observation for a specific variable, showing its influence on the model's output. The colour indicates the feature value, with blue dots representing lower values and red dots representing

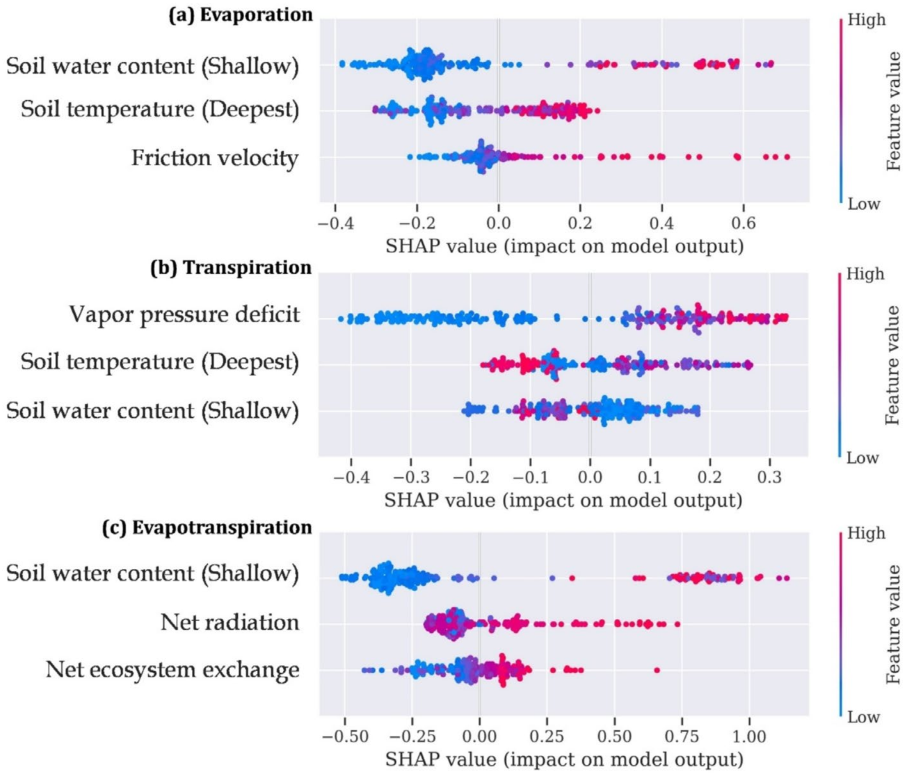

FIGURE 6 | Summary plot shows the impact of the model output of three components (a, evaporation; b, transpiration and c, evapotranspiration) for the three most crucial variables.

higher values of the variable itself. For evaporation (Figure 6a), soil water content has the highest impact, with higher SHAP values linked to increased evaporation, while lower soil moisture reduces the model predictions of evaporation. However, the physical effect of low soil moisture can still increase evaporation due to elevated VPD. Soil temperature and friction velocity are also important factors, with friction velocity boosting evaporation predictions by enhancing air mixing. In transpiration (Figure 6b), VPD emerges as the key variable reducing SHAP values, emphasising its role in lowering transpiration predictions. At the same time, soil temperature and soil water content positively influence the model's ability to predict transpiration. For ET (Figure 6c), shallow soil water content dominates the predictions, followed by net radiation and NEE, which significantly impact ET.

Soil moisture is essential for maintaining evaporation by continuously supplying water, while friction velocity promotes air mixing, helping to move water vapour from the soil to the atmosphere (Gentine et al. 2011). VPD is crucial for transpiration, as higher VPD increases plant water loss, potentially leading to stomatal closure and reduced carbon dioxide uptake (Kolb and Sperry 1999; Brabec et al. 2017; Gu et al. 2018). Net radiation supplies the energy necessary for ET processes, while NEE influences stomatal behaviour and plant water use, both of which are key to ET dynamics (Wang et al. 2021).

4 | Conclusions

This study refines ET partitioning, demonstrating that soil properties (shallow water content and deepest layer temperature), friction velocity, VPD, net radiation and NEE are crucial for accurate predictions. Our model offers novel insights into ET dynamics by incorporating hydrometeorological and biomass productivity variables. Our framework highlights the importance of integrating hydrometeorological and biomass productivity variables to predict the ET and its components. The RF model's performance (KGE score) demonstrates that the variable's value combination achieves the highest accuracy for ET (KGE: 0.865) and outperforms models using only hydrometeorological or biomass productivity variables. The SHAP analysis identified the 10 most important variables, with soil properties and friction velocity controlling evaporation. Transpiration was driven by VPD and soil properties and ET by shallow soil water content, net radiation and NEE.

Even though our study is based on flux tower data, our variable importance analysis indicates that the framework can still be implemented in data-scarce settings as long as the key variables, such as soil moisture, temperature and VPD, are available. This, however, does not undermine the need for exhaustive validation in data-scarce settings to ensure accuracy. The future scope includes testing a diverse range of ML models, expanding the current framework multi-site and implementing complementary mechanistic modelling of the ET partitioning process.

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data used in this study are available through AmeriFlux at https://ameriflux.lbl.gov/.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section.