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Key Points:

- Three Evapotranspiration (ET) partitioning methods were used to partition ET in differently managed wheat systems
- Grazing altered the relation between T:ET and enhanced vegetation index
- ET partitioning errors were higher in disturbed (i.e., grazed) systems

Supporting Information:

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

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Vegetation Index-Based Partitioning of Evapotranspiration Is Deficient in Grazed Systems

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Abstract Partitioning evapotranspiration (ET) into its primary components, that is, evaporation (E) and plant transpiration (T), is needed in a range of hydrometeorological applications. Using vegetation index (VI) to obtain spatially resolved T:ET ratio over large areas has emerged as a promising approach in this regard. Here, we assess the effectiveness of this approach in differently managed wheat systems. Results show a weak relation between T:ET and VI in disturbed (i.e., grazed) systems. Furthermore, flux partition based on a canonical T:ET versus VI relation or the relation derived in a neighboring undisturbed wheat system introduce large errors in disturbed systems, thus underscoring the limits on the transferability of the VI-based ET partitioning approach. The effectiveness of the VI-based approach is found to be related to the strength of correlation between VI and vapor pressure deficit and/or radiation. This correlation metric can help identify settings where the approach is likely to be effective.

Plain Language Summary Evapotranspiration (ET) plays a significant role in water and climate cycles by affecting the energy and water balance over the land surface which in turn mediates the land-atmosphere interactions. ET is composed of two primary components that is, direct evaporation (E) and plant transpiration (T). Partitioning total ET into its individual components (E and T) is of significant importance for better assessment of both regional and global water budgets. One of the primary approaches to partition ET over large areas is by using vegetation indices (VI), which indirectly capture plants' biophysical state. This approach has been used to partition ET in different landscapes, but its efficacy has not been tested in disturbed ecosystems, which cover a large fraction of Earth's vegetated area. Here, we assess the effectiveness of this VI-based ET partitioning approach in disturbed (i.e., grazed) ecosystems. We find that the VI-based ET partitioning introduces large errors in disturbed systems. Further investigation identifies conditions that can be used to filter-out regions where the VI-based partition is likely to be more (or less) effective.

1. Introduction

Around 60% of the precipitated water is returned to the atmosphere by evapotranspiration (ET) (Oki & Kanae, 2006). Unsurprisingly, ET plays a major role in influencing the water and climate cycles components at both local and global scales (Bonetti et al., 2015; Condon & Maxwell, 2019; Jung et al., 2010; Oishi et al., 2010; R. Wang et al., 2013; Zhang et al., 2016). To assess these influences, it is crucial to partition ET into its components, viz. evaporation (E) from bare soil and wet plant surfaces, and plant transpiration (T). This is especially needed as relative contributions of E and T vary in space and time, in part due to the varied controls on E and T (Ritchie & Burnett, 1971; Unkovich et al., 2018). For instance, in addition to the meteorological, soil, and plant morphometric properties that influence E, T is also majorly influenced by plant physiology (Y. Liu et al., 2017, 2020; X. Sun et al., 2019; Wang & Liu, 2007). Partitioning of ET can facilitate understanding of plants' water use strategies and their responses to environmental forcings, help assess the role of changes in land cover on ET, and improve predictions of hydrological responses as moisture used for E and T are usually derived from different soil stores (Alkama & Cescatti, 2016; X. Chen et al., 2015; Perez-Priego et al., 2018; Raghav & Kumar, 2021; Zeng et al., 2017).

Over the past years, several methods have been developed for ET partitioning to improve our understanding of the dynamics of T over ET (T:ET hereafter). Broadly, these methods can be categorized as direct and indirect. Direct methods use in situ observations of the water fluxes (i.e., E, T, and/or ET), and include eddy covariance (EC)

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data based partitioning, sap flux and/or micrometeorological techniques (Cammalleri et al., 2013), microlysimeters and/or chambers (Yaseef et al., 2010), and techniques based on stable isotopes in the water fluxes (Ferretti et al., 2003; Williams et al., 2004; Xiao et al., 2018). Details on these various methods of partitioning and their challenges are well documented elsewhere (Kool et al., 2014; Stoy et al., 2019). Majority of the methods listed above provide T:ET estimates at the gauging sites (e.g., Black et al., 1969; Li et al., 2019; Nelson et al., 2020; Paul-Limoges et al., 2020; Perez-Priego et al., 2018; Scanlon & Sahu, 2008; Scott & Biederman, 2017; Zhou et al., 2016) or over its flow contribution area (e.g., Good et al., 2015; Jasechko et al., 2013). To obtain spatially explicit estimates of T:ET, numerous alternative indirect methods have been developed. For example, Long and Singh (2012) and Zhang et al. (2019) used a remote sensing approach to partition ET. Land surface modeling (e.g., Dirmeyer et al., 2006; Fatichi & Pappas, 2017; Haddeland et al., 2011; Lian et al., 2018; Paschalis et al., 2018) and hybrid approaches (e.g., Martens et al., 2017; Miralles et al., 2011) have also been used to obtain T:ET estimates over large areas. Recently, parsimonious models that only use widely available vegetation indices to obtain T:ET at multiple temporal scales (e.g., weekly, monthly, seasonal) has received significant attention (e.g., Berkelhammer et al., 2016; Fatichi & Pappas, 2017; S. Kang et al., 2003; L. Wang et al., 2014; Wei et al., 2015, 2017). These models are able to explain a significant fraction of variability in T:ET using vegetation indices such as leaf area index (LAI) and enhanced vegetation index (EVI). For example, based on a meta-analysis, Wei et al. (2017) reported that T:ET can be well represented as a function of LAI ($R^2 = 0.87$) in cropland settings. Zhou et al. (2016) showed that T:ET is strongly related to EVI ($R^2 = 0.85$) at eight-day scale based on the concept of underlying water use efficiency (uWUE). S. Kang et al. (2003) also reported a close relation between T:ET and LAI ($R^2 = 0.97$) in a winter wheat system based on lysimeter data. L. Wang et al. (2014) concluded that LAI and growth stage function can be used to obtain global T:ET estimates.

Notably, the efficacy of vegetation index based approach has not been tested in disturbed ecosystems or ecosystems that experience impulse alterations in canopy cover, such as due to grazing management, thinning, hurricanes, and wildfires. We furnish this gap by evaluating the relation between T:ET and vegetation index in both undisturbed and disturbed wheat systems. Here, the disturbance is introduced due to grazing management. In addition, we assess the conditions that facilitate a stronger correlation between T:ET and vegetation index. The paper is organized as follows: Section 2 provides a detailed description on the materials and methods used in this study. Results on the flux partitioning are presented in Section 3.1. Section 3.2 presents the results on the relationships between T:ET and EVI. The errors statistics in the prediction of T:ET using EVI at different time scales are presented in Section 3.3. Section 4.4 assesses the controls on T:ET versus vegetation index relation.

2. Materials and Methods

2.1. Study Sites

Two years of data from three neighboring, but differently managed, winter wheat cropping fields (Sites 1–3 hereafter) were used (Figure 1 and Figure S1 in Supporting Information S1). Each field (cropped area ranging from ~13 to 22 ha) had identical soil type, experienced similar climatology, and the wheat seeds were sown at about 19 cm row spacing in each field. These fields are part of the United States Department of Agriculture, Agricultural Research Service, Grazinglands Research Laboratory's flux network (GRL-FLUXNET), which is a dense network of 16 Eddy Covariance (EC) towers in central Oklahoma (El Reno), USA. During the 2016–2017 growing season (October 2016–May 2017), grain-only and graze-grain wheat were grown at sites 1 and 3, respectively. Grain-only wheat has a single purpose to produce wheat grains, while graze-grain wheat has a dual purpose as it serves as a pasture for grazing cattle from November to February and is used for producing wheat grains thereafter. As data of differently managed configurations are only available for wheat, we restrict this study to wheat crops. Hence, 2016–2017 data from site 2, where Canola was grown, was not considered. In the 2017–2018 growing season, site 1 had graze-grain wheat, site 2 had grain-only wheat, and site 3 had graze-out wheat. Graze-out is also a single purpose crop that is grown for the entire season to solely serve as a pasture for the grazing cattle. The 2017–2018 growing season data from all three sites were used for analyses.

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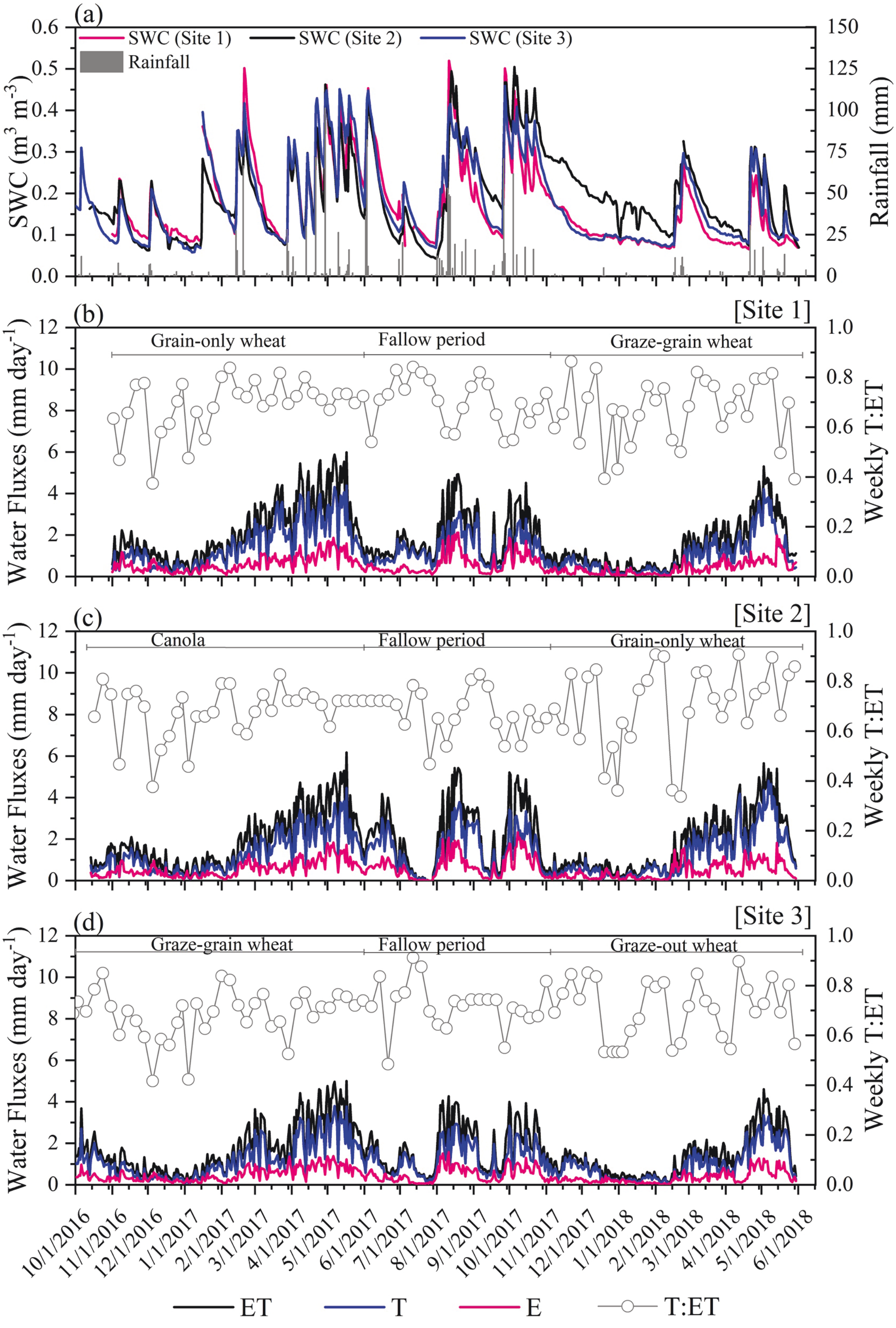

Figure 1. (a) Daily variations of rainfall and soil water content at each site, (b–d) daily variations of total evapotranspiration (ET), transpiration (T), and direct evaporation (E) based on flux variance similarity method at three different sites. Open circles plotted on the secondary Y-axis show the ratio of weekly T and ET. Notably, all three sites underwent crop rotation. Fallow period and canola were not considered for analyses in this study.

2.2. Data

2.2.1. Eddy Covariance and Ancillary Hydro-Meteorological Data

Water vapor and carbon dioxide fluxes were measured in all three wheat fields for the 2016–2017 and 2017–2018 growing seasons using eddy covariance (EC) systems. The data were recorded at 10 Hz frequency (i.e., 10 measurements per second) and then processed in the EddyPro software to get good quality estimates of latent heat fluxes at 30 min intervals. All the EC towers were located in the middle of respective fields. Measurement height of the EC system installed on the tower was about 2.5 m for all the sites. This resulted in fetch length to be around 100 m for more than 80% of the time during the growing period. More details on the EC data collection and processing can be found in Wagle et al. (2018, 2019).

Ancillary hydro-meteorological variables such as net radiation, soil water content (~5 cm depth), air temperature, soil heat flux, soil temperature, relative humidity, incoming photosynthetic photon flux density, and infrared surface temperature were also measured at the sites. We obtained rainfall data from the Oklahoma El Reno Mesonet station (located within 1–1.5 km from the study sites).

2.2.2. Remote-Sensing Data

The EVI for the three differently managed wheat systems, that is, grain-only, graze-grain, and graze-out, were derived (Figure S2 in Supporting Information S1) at 30 m spatial resolution using the Landsat surface reflectance images from both Landsat 7 ETM+ and Landsat 8 obtained from the U.S. Geological Survey (USGS) Earth Explorer. The EVI of individual pixels were spatially averaged for each field using ENVI software. The derived EVI data has a temporal resolution of 8 days (Figure S2 in Supporting Information S1). Data quality flag was used to select pixels within a field for any given date for further analyses. The EVI for each pixel was calculated following Jiang et al. (2008):

$$EVI = \frac{G \cdot (NIR - R)}{NIR + C1 \cdot R - C2 \cdot B + L} \tag{1}$$

where G (=2.5) is a gain factor. $C1$ (=6) and $C2$ (=7.5) are band-specific correction coefficients of aerosol resistance term. L (=1) is background brightness correction factor. NIR, R, and B are the near-infrared, red, and blue bands, respectively.

2.3. ET Partitioning

Total ET was partitioned into T and E based on three methods using the EC data sets: flux variance similarity (FVS) theory-based method (Scanlon & Sahu, 2008), the uWUE method (Zhou et al., 2016), and the transpiration estimation algorithm (TEA) method (Nelson et al., 2018). Consideration of multiple methods for this study was driven by the fact that estimates from no one method is generally considered perfect, and each of them are affected by inherent assumptions in them.

The FVS method can simultaneously partition ET and net ecosystem CO_2 exchange (NEE) into their primary components, that is, T and E for ET, and photosynthesis and respiration for NEE, based on the correlation between high-frequency EC measurements of carbon dioxide and water vapor fluxes along with measured or estimated leaf-scale water use efficiency (WUE) (Scanlon & Kustas, 2010, 2012; Scanlon & Sahu, 2008; Scanlon et al., 2019). Readers may refer to Text S1 in Supporting Information S1 and references therein for the mathematical formulation of FVS theory. The method has shown promising results in different land cover settings (Peddinti & Kambhammettu, 2019; Rana et al., 2018;Scanlon & Kustas, 2012; Sulman et al., 2016; Wagle et al., 2020; Wagle, Gowda, et al., 2021; L. Wang et al., 2010; W. Wang et al., 2016), including cropped systems such as rainfed alfalfa field (Wagle et al., 2020), Mediterranean cropping system (Rana et al., 2018), wheat (a $C3$ crop) (Scanlon & Sahu, 2008), corn (a $C4$ crop) (Scanlon & Kustas, 2010), and several others (Wagle, Skaggs, et al., 2021). One of the critical inputs to FVS method is the leaf-scale WUE. In the absence of direct measurements, leaf-scale WUE can be estimated as below:

$$WUE = \left(\frac{1}{DR}\right) \cdot \left(\frac{c_a - c_i}{q_a - q_i}\right) \tag{2}$$

where DR (=1.6) is the ratio of molecular diffusivities for water and carbon concentrations through the stomatal aperture (Massman, 1998). c_a (q_a) and c_i (q_i) are the ambient and intercellular concentrations of carbon (water), respectively. Here, c_a and q_a can be derived by extrapolating the logarithmic mean profile of EC measurements of carbon dioxide and water vapor fluxes with stability correction to zero displacement height (Brutsaert, 2013; Scanlon & Sahu, 2008). q_i is usually estimated assuming 100% relative humidity at leaf temperature (approximated as ±2°C of the air temperature). c_i can be modeled in different ways in Fluxpart (Wagle, Skaggs, et al., 2021). Based on the findings of Wagle, Skaggs, et al. (2021) for wheat, we choose a constant ratio method where c_i/c_a is assumed to be constant (K); with $K = 0.7$ for $C3$ plants (Sinclair et al., 1984) and $K = 0.44$ for $C4$ plants (Kim et al., 2006).

Water flux partitioning based on uWUE concept was proposed by Zhou et al. (2016). Herein, partitioning is performed based on uWUE, which is obtained using gross primary productivity (GPP) and vapor pressure deficit (VPD) based on Zhou et al. (2014):

$$uWUE = \frac{GPP \cdot \sqrt{VPD}}{ET} \tag{3}$$

T:ET is estimated as:

$$\frac{T}{ET} = \frac{uWUE_a}{uWUE_p} \tag{4}$$

where uWUE$_a$ is the apparent uWUE and uWUE$_p$ is the potential uWUE. uWUE$_a$ is estimated directly from Equation 3 if partitioning needs to be obtained at half-hour resolution. For estimates at coarser resolution (say a week or coarser), a linear regression between $GPP \cdot \sqrt{VPD}$ and ET is obtained using data derived through averaging of participating variables using a moving window approach. uWUE$_p$ represents the maximum carbon gain to water loss and is estimated using 95th quantile regression between $GPP \cdot \sqrt{VPD}$ and ET for a given year or season. The key assumption of uWUE-based method is that uWUE$_p$ is constant for a given year or season and calculation of uWUE$_p$ is based on periods when $T \approx$ ET or $E \approx 0$. uWUE-based method is very straightforward in nature and easy to use. This approach has been used to partition water fluxes in different biomes (Bai et al., 2019; Hu et al., 2018; Nelson et al., 2020; J.-Y. Sun et al., 2020; Xu et al., 2021; Zhou et al., 2016, 2018).

TEA method is a nonlinear machine learning method for water flux partitioning Nelson et al. (2018). TEA method predicts the T using a Random Forest (RF) regressor which is trained for ecosystem WUE (=GPP/ET) during dry periods of growing season that is, during periods when $E \approx 0$ or in other words the RF model is trained for GPP/T. The dry periods are selected by filtering out the wet periods from the time series based on rainfall and ET inputs. To ensure the good quality data for training the model, various quality control steps are performed, as detailed in Nelson et al. (2018). The trained model on the filtered data is then used to predict GPP/T for the full time series. TEA method has been shown to perform well across different ecosystems (Hu & Lei, 2021; Migliavacca et al., 2021; Nelson et al., 2018, 2020; Räsänen et al., 2020).

2.4. Modeling T:ET Ratio

Partitioning using all three methods was performed for two growing seasons (2016–2017 and 2017–2018) at three wheat sites. As site 2 had Canola planted in 2016–2017 (Figure 1), it was not considered in this study. The three partitioning methods have different data requirements to model T:ET. Partitioning from FVS method was performed using 10 Hz frequency EC data using Fluxpart version 0.2.10 (Skaggs et al., 2018). Partitioning from uWUE and TEA methods were performed using the 30 min interval flux data, which was obtained by processing high frequency EC data in EddyPro software (Wagle et al., 2018). The flux data was also processed with CO_2 flux partitioning (i.e., NEE to GPP and ecosystem respiration (R_{eco})) and gap filling using REddyProc package in R (Reichstein et al., 2005; Wutzler et al., 2018). Partition estimates were obtained at 30 min interval using all three methods. Fluxpart may fail to produce outputs for a certain intervals because of various physical constraints (Palatella et al., 2014; Scanlon et al., 2019; Wagle, Skaggs, et al., 2021). Other two methods may also produce erroneous values of T:ET for certain time periods. We only used reliable estimates of T:ET, and filtered out the bad quality estimates following the rubric detailed in Nelson et al. (2018) and Zhou et al. (2016). Also, the hours with rainfall were removed from the analysis as partitioning estimates during it are expected to be unreliable. Overall, the application of aforementioned quality constraints resulted in 50%, 52%, and 81% of the data being suitable for further analyses for FVS, uWUE, and TEA methods, respectively. To obtain T:ET at weekly and monthly scales, weekly mean diurnal cycles were used. For example, to calculate the T:ET for a particular week, mean diurnal variations of T and ET at half-hour resolution were generated for the week, and then T:ET was determined by summing half-hourly binned mean T and mean ET. The resultant weekly average T:ET (a constant ratio for a week) was used to partition EC-measured daily ET values into daily E and T values. Seasonal T:ET was evaluated using seasonal T and ET estimates, which were obtained by summing individual daily estimates over a season.

2.5. Deriving T:ET Versus EVI Relation

Following the lead of previous studies (Lian et al., 2018; L. Wang et al., 2014; Wei et al., 2015, 2017), we derived a power-law relation (T:ET = $a\mathrm{EVI}^b$) between Landsat-derived EVI and weekly averaged T:ET from all the ET partitioning methods in all three wheat systems, that is, grain-only, graze-grain, and graze-out. As has also been done in the previous studies, binning of T:ET was carried out to reduce the effects of confounding variables (e.g., rainfall, available energy) on the emergent T:ET-EVI relation during the growing period. Best fit parameters a and b for each system were obtained by performing a nonlinear regression analysis using nonlinear least squares method in *R* (Bates & Watts, 1988; Elzhov et al., 2010).

3. Results and Discussion

3.1. Temporal Variations in T:ET

Weekly T:ET ratios were obtained for all three wheat sites for 2016–2018 using the three ET partitioning methods (see Figure 1, Figures S3 and S4 in Supporting Information S1). ET fluxes were larger during the 2016–2017 growing season than the 2017–2018 growing season at each site, in part because the former received much more rainfall. For example, total seasonal ET, that is, ET during November–May in 2016–2017 (2017–2018) for grain-only and graze-grain wheat were ∼460 mm (∼345 mm) and ∼367 mm (∼287 mm), respectively. Corresponding precipitation totals for the two seasons were 501 and 155 mm, respectively. Notably, the change in T:ET between the two seasons was modest with its magnitude being 0.71 (0.74) and 0.70 (0.7) in grain-only and graze-grain wheat in 2016–2017 (2017–2018) based on FVS method. Corresponding seasonal T:ET estimates using uWUE method were 0.58 (0.58) and 0.54 (0.55) in grain-only and graze-grain wheat. TEA method yielded seasonal T:ET of 0.80 (0.78) and 0.74 (0.76). Seasonal T:ET estimates obtained here, based on TEA and FVS methods, are consistent with other studies for winter wheat. For example, Ma and Song (2019) reported a seasonal T:ET of 0.75 based on the traces of stable isotopes. Yu et al. (2009), S. Kang et al. (2003), and C. Liu et al. (2002) reported a seasonal T:ET ranging between 0.67 and 0.75 based on microlysimeters. Notably, uWUE method shows a lower T:ET estimate with respect to TEA and FVS methods. The small difference in T:ET across the 2 years and wheat systems is consistent with the findings of past studies (Good et al., 2017; Nelson et al., 2020; Wagle, Gowda, et al., 2021), which attribute it to the reduction in canopy cover when faced with limiting resources, and to the compensating effect of E from wet canopies (intercepted rainfall) versus that from wet soil with changes in canopy cover. The T:ET was, however, found to be highly variable within the season (Figure 1). Weekly mean and coefficient of variation of T:ET, based on FVS method, were 0.63 (0.67) and 13.95% (20.33%), respectively, in 2016–2017 (2017–2018) at the grain-only site. The corresponding values for the graze-grain site were 0.62 (0.66) and 14.95% (14.45%). The intra-seasonal variations are attributable to a variety of hydroclimatic variables (e.g., rainfall, atmospheric water demand, available energy, and soil moisture). Overall, VPD, especially, had a strong control on T:ET variations with low T:ET values at low VPD and high values at high VPD. For example, average T:ET in grain-only wheat was 0.52 for low VPD values (VPD less than 25th percentile) and T:ET was 0.84 for high VPD values (VPD larger than 75th percentile). This is largely because seasonal VPD is correlated with increasing LAI. Larger biomass decreases the amount of radiative energy available for soil evaporation due to increased shading. At the same time, it also contributes to increase in transpiration. These result in higher T:E, and consequently T:ET, later in the growing season when the VPD is also higher. Another contributor to this variation is the occurrence of lower VPD periods post precipitation or dewfall during which soil is usually wet and T:ET is diminished (X. Sun et al., 2019). For example, T:ET was around 0.52 during rainy days as compared to 0.70 during non-rainy days in January 2017 (EVI is low during this period) for grain-only system. This is true

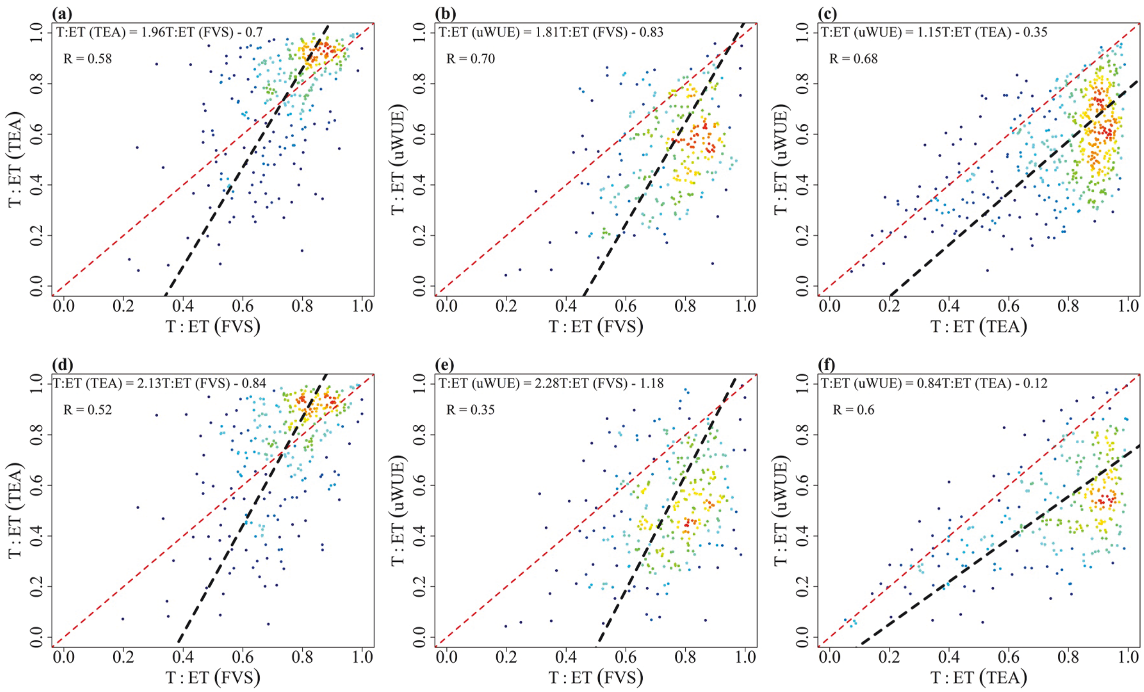

Figure 2. Intercomparison of the three evapotranspiration (ET) partitioning methods, viz. (a) T:ET (FVS) to T:ET (TEA), (b) T:ET (FVS) to T:ET (uWUE), and (c) T:ET (TEA) to T:ET (uWUE), at daily temporal resolution for the three sites. Panels (d–f) are similar to panels (a–c), respectively, but show the comparison only for the periods when ET partitioning estimates were available from all the three methods. *R* represents the Pearson correlation coefficient. The black dashed lines are the best fit linear lines estimated using orthogonal-least-squares regression (S. Chen et al., 1989). Notably, the data used for intercomparison only includes the period during which T:ET estimates are available for both the intercomparing methods. Colors of the data points represent the relative point density with warmer colors indicating higher density.

even for peak wheat growth period (Mid-March, 2017 to Mid-April, 2017; EVI is high during this period) when T:ET was about 0.64 during rainy days as compared to 0.82 during non-rainy days. During post precipitation time intervals, wetness of the top soil may enhance *E* more than *T*, as the root zone moisture available for transpiration may still be deficient. Furthermore, wetness on the leaves during these times may inhibit transpiration (Good et al., 2017; X. Sun et al., 2019). Notably, the increasing T:ET with VPD over a growing season, which is a result of covariation of multiple other variables as noted above, is in contrast to the expected T:ET variations with VPD for the scenario with negligible difference in LAI and other meteorological conditions.

Intercomparison of all the three methods for ET partitioning shows that there is agreement among the methods in regards to capturing the overall temporal pattern of T:ET, with a correlation of 0.58 between FVS and TEA, 0.70 between FVS and uWUE, and 0.68 between TEA and uWUE (Figure 2). Overall, uWUE method shows lower T:ET (with average T:ET = 0.54) as compared to T:ET estimates from FVS method (with average T:ET = 0.75), while the TEA method was in good agreement (with average T:ET = 0.76) with FVS method. These results for TEA and uWUE are in agreement with Nelson et al. (2020) where uWUE method also produced lower T:ET estimates as compared to the TEA method.

3.2. Relation Between T:ET and EVI

Following the method described in Section 2.5, the relation between T:ET and EVI was developed. We found that the EVI could explain most of the variability (44%–78%) in T:ET in grain-only wheat (Figures 3a, 3d and 3g). This is consistent with other studies (S. Kang et al., 2003; Wei et al., 2017; Zhou et al., 2016) that reported a very strong positive correlation between vegetation indices and T:ET. However, this relation was not strong for graze-grain and graze-out wheat systems (Figure 3). As each ET partitioning method has its inherent assumptions and associated limitations, similar evaluations were performed using periods for which ET partitioning estimates were available for all methods (Figure S5 in Supporting Information S1). These results also indicate

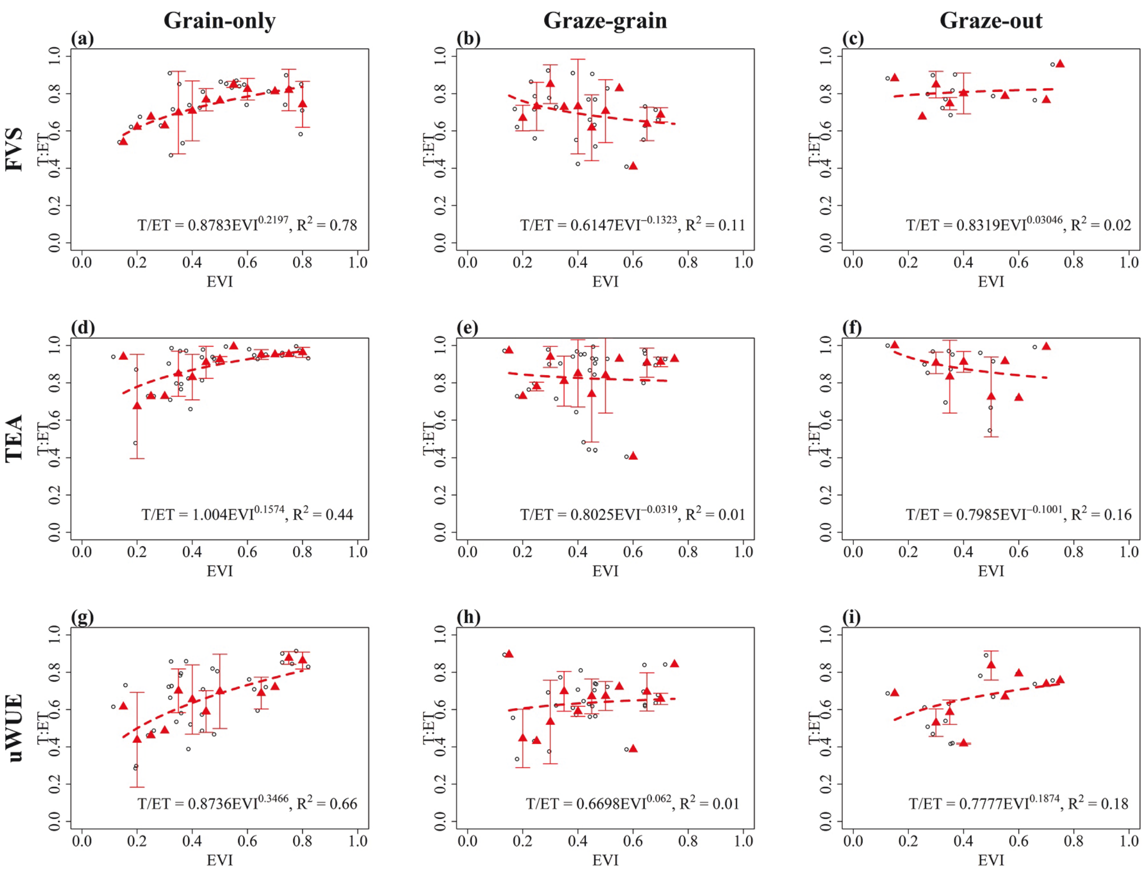

Figure 3. Relations between T:ET and enhanced vegetation index (EVI) in differently managed winter wheat systems using the three ET partitioning methods; (a–c) flux variance similarity, (d–f) transpiration estimation algorithm, and (g–i) underlying water use efficiency. Gray dots are weekly T:ET, ±3 days around the Landsat image acquisition date, during mid-day (11 a.m.–2 p.m.). Red triangles are averaged T:ET corresponding to 0.05-bin EVI. The vertical lines are the error bars of mean T:ET for each bin. The red dash line in each panel is the best nonlinear fit between triangles and corresponding EVI.

that T:ET-EVI relation was strong in grain-only wheat but this relation became weak for the grazed systems. In the following section, we explore this aspect in more detail.

3.3. Errors in the Prediction of T:ET Using EVI

The applicability of previously reported canonical relations between EVI and T:ET for crop systems was first assessed in both disturbed (i.e., grazed) and undisturbed (i.e., non-grazed) systems. To this end, the global crop relation (T:ET = $0.66\text{LAI}^{0.18}$) presented in Wei et al. (2017) was used. LAI was obtained from EVI based on Y. Kang et al. (2016). Results (Figure 4d) show that Mean Absolute Percentage Error (MAPE) (see Text S2 in Supporting Information S1 for additional details regarding the calculation of MAPE) which was calculated using the predicted (i.e., T:ET obtained using the global crop relation (i.e., T:ET = $0.66\text{LAI}^{0.18}$) of Wei et al. (2017) in different systems) and observed (i.e., T:ET obtained using FVS method) T:ET, was significantly worse for disturbed systems at both weekly and monthly scales. Notably, the errors are larger (Figures 4a–4c) even when the T:ET versus EVI relations derived at the neighboring undisturbed site (i.e., site corresponding to grain-only wheat system) is used from all the methods. For example, at weekly scale, MAPE was highest (about 20%) for graze-grain case and lowest (about 9%) for grain-only case for FVS-method (Figure 4a). Similar results were also observed at monthly scales, and for other partitioning methods. We also evaluated the errors in each wheat system when using T:ET-EVI relations obtained in a differently managed system (see Table 1). Errors generally increased, with a few exceptions, when the T:ET-EVI relation developed for a wheat system is used for other at both weekly and monthly scales. Although the three sites are all winter wheat systems that experience similar hydroclimatology, the difference in management implementations make them act differently in regards to T:ET dynamics vis-a-vis EVI. Among the different temporal scales, errors were minimum at the seasonal scale.

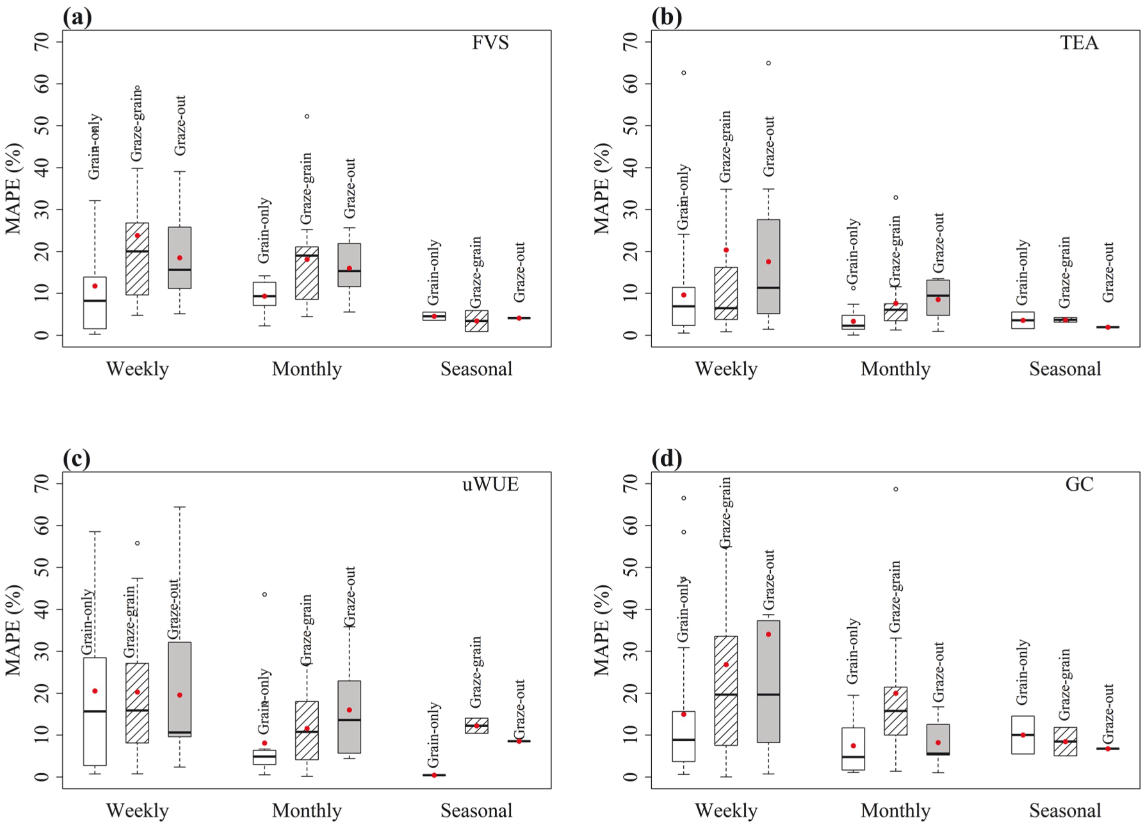

Figure 4. Mean absolute percentage error (MAPE) of predicted T:ET using the relations developed in unmanaged system from (a) flux variance similarity (FVS) method, (b) transpiration estimation algorithm method, and (c) underlying water use efficiency method at weekly, monthly, and seasonal time scales for winter wheat systems with varied management implementations. (d) An additional evaluation is performed using a relation (hereafter referred as GC) derived using global data over varied crops as presented in Wei et al. (2017). MAPE calculation in panels (a–c) used T:ET obtained using the respective partitioning method. In panel (d), T:ET were estimated using the FVS method. Red dots represent the average MAPE.

Table 1
Average Mean Absolute Percentage Error (%) When Using T:ET-Enhanced Vegetation Index Relations Obtained in Different Wheat Systems and the Global Crop Relation Presented in Wei et al. (2017)

	MAPE (%)								
	Weekly			Monthly			Seasonal		
T:ET-EVI relation	G	GG	GO	G	GG	GO	G	GG	GO
FVS (G)	11.76	23.84	18.50	9.33	18.12	16.01	4.55	3.42	4.09
FVS (GG)	20	17.67	12.1	15.97	15.53	9.23	2.61	2.04	2.67
FVS (GO)	19.16	32.54	8.96	8.36	20.91	7.92	15.43	13.55	12.75
TEA (G)	9.62	22.36	17.56	3.34	7.66	8.56	3.58	3.70	1.94
TEA (GG)	14.51	21.44	15.62	10.95	8.71	9.33	8.3	5.29	4.29
TEA (GO)	15.26	21.42	14.11	9.94	8.60	6.07	3.16	0.40	1.64
uWUE (G)	20.55	20.27	19.57	8.13	11.59	16.01	0.45	12.23	8.55
uWUE (GG)	27.65	30.13	26.58	29.54	26.98	30.87	29.61	27.54	26.97
uWUE (GO)	23.57	28.88	25.67	26.0	24.13	28.93	26.79	25.08	24.78
GC	14.99	26.84	34.06	7.46	20.00	8.24	10.04	8.47	6.77

Note. Here, G represents grain-only wheat system, GG represents graze-grain wheat system, GO represents graze-out wheat system, and GC represents the global crop relation.

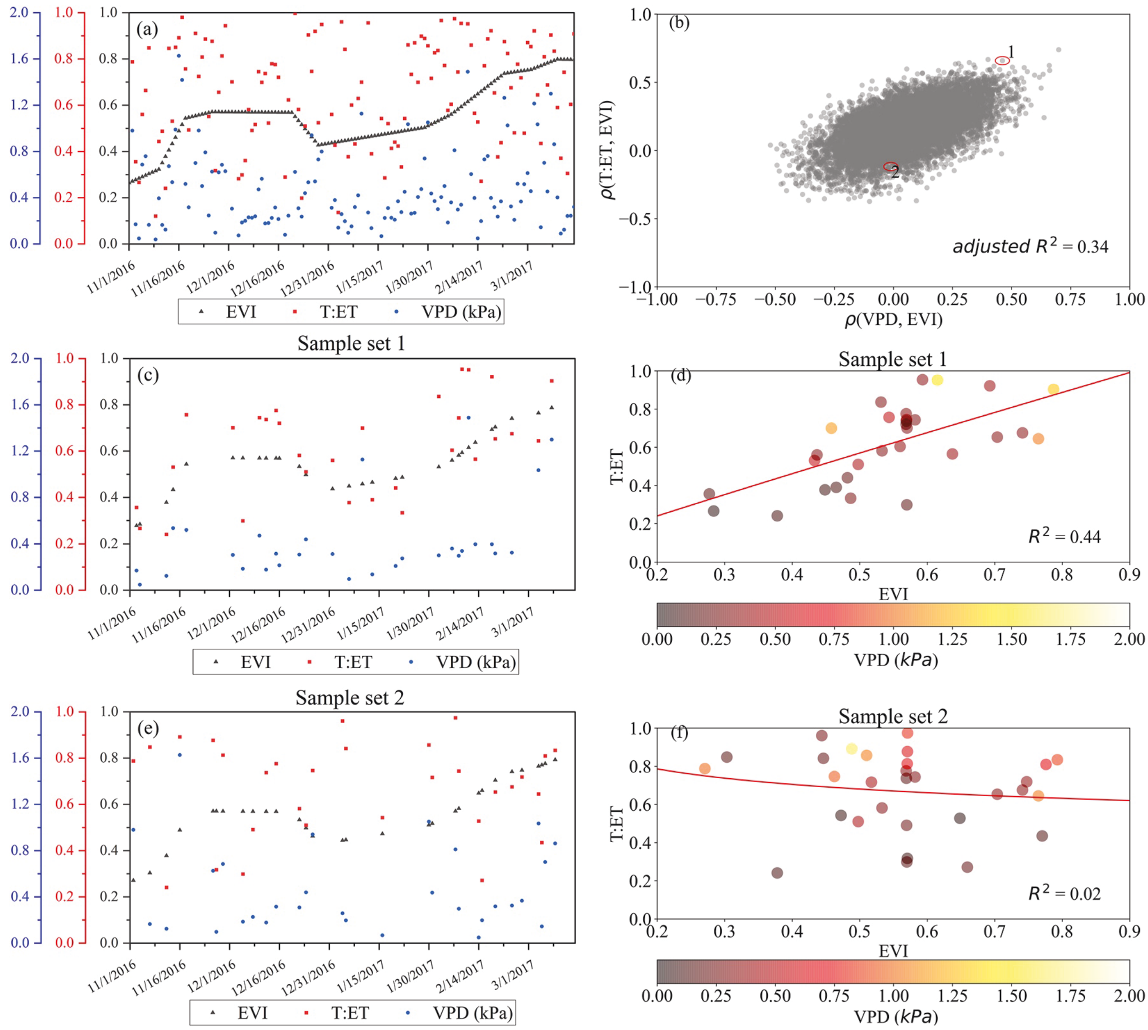

Figure 5. Temporal variations of enhanced vegetation index (EVI), flux variance similarity (FVS)-derived T:ET, and (a) vapor pressure deficit (VPD) for all days, (c) sample set 1, and (e) sample set 2. (b) Scatter of correlation between VPD and EVI and correlation between FVS-derived T:ET and EVI for 10,000 sample sets with each set having randomly selected 30 days. Scatter between FVS-derived T:ET and EVI for (d) sample set 1 and (f) sample set 2. Red solid lines in panels (d and f) represent the best-fit nonlinear lines.

Smaller error at the seasonal scale is consistent with other studies which reported that T:ET are uncorrelated with vegetation growth across sites (Fatichi & Pappas, 2017; Nelson et al., 2020).

We further investigated the possible causes for the lack of strong relation between T:ET and EVI in graze-grain and graze-out systems. At ecosystem-scale, T rate is controlled by meteorological conditions, the stomatal conductance (g_s), and plant's biophysical state (e.g., LAI, EVI, etc.). T is usually proportional to $g_s \times$ LAI $\times$ VPD. g_s is affected by multiple environmental variables, including VPD, soil moisture, radiation, and air temperature (Daly et al., 2004; Jarvis, 1976) (see Text S3 and Figure S11 in Supporting Information S1). Given our earlier result that showed a strong influence of VPD on T:ET (in Section 3.1), we started with a hypothesis that the increase in T:ET with EVI in undisturbed systems is strongly influenced by the covariation of VPD and EVI. Any disturbance or grazing management may, however, disturb the co-variation of EVI with VPD, thus also impacting the covariation of T:ET with EVI. To test this hypothesis, we obtained relations between EVI and T:ET for 10,000 different sample sets of randomly distributed 30 days from the growing season (Figure 5a) in the undisturbed system. Each set covers a wide enough range of EVI that is experienced in grain-only and graze-grain systems. The orientation of the point cloud along 1:1 direction in Figure 5b confirms that the relation between EVI and T:ET is stronger with higher correlation between VPD and EVI. To parse this further, we selected two sample sets with contrasting correlations between T:ET and EVI. Sample set 1 has ρ(T:ET, EVI) of 0.66 and sample set 2 has

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ρ(T:ET, EVI) of −0.12. Here ρ is the coefficient of correlation. The results suggest that if EVI is not co-varying closely with VPD (sample set 2, see Figure 5e), then the relation between T:ET and EVI is not strong (Figure 5f). But if EVI co-varies closely with VPD, then the T:ET-EVI relation improves (see Figures 5c and 5d). In fact, at the unmanaged site where a strong T:ET-EVI relation is obtained (see Figure 1), the correlation between VPD and EVI until the peak growth period is 0.60. In contrast, the corresponding value for graze-grain and graze-out cases were 0.15 and −0.36, respectively. Similar evaluations were also conducted for uWUE (see Figure S9 in Supporting Information S1) method and TEA method (see Figure S10 in Supporting Information S1). The results in Figure 5, which are based on FVS-derived T:ET, also hold for the other methods (Figures S9 and S10 in Supporting Information S1). Furthermore, evaluations were also conducted for soil moisture, radiation, and air temperature, variables known to affect the stomatal conductance (see Figures S6–S8 in Supporting Information S1). Results indicate that the covariation of solar radiation with EVI also explained the covariation of T:ET with EVI, although the relation was less stronger. The influences of air temperature and soil moisture were much less (see Figures S7 and S8 in Supporting Information S1). These results indicate that the expressed T:ET-EVI relation works best with systems with a clear seasonal phenology, which usually results in improved correlation with VPD, provided VPD also exhibits an overall increasing trend during the growing season. When crop fields are grazed, plant development cycle or the phenology gets decoupled with the overall seasonal variation of VPD and radiation, thus limiting its explanatory power for seasonal T:ET variations. This is consistent with the reported poor explainability of T:ET by vegetation indices in grasslands and needle leaf forests (Zhou et al., 2016), that also lack distinct seasonal phenologies. Simulations based on a two-source ET model further corroborate the role of covariation between EVI and VPD on the strength of T:ET relation (see Text S4 and Figure S13 in Supporting Information S1). The two-source ET model elucidates the dependence of T:ET on both vegetation index and meteorological variables, including LAI (or EVI), VPD, solar radiation, soil moisture, etc. (see Equations 10a–10l in Supporting Information S1). Figures S14–S17 in Supporting Information S1 further highlight that T:ET is strongly affected by LAI (or EVI) variation, with it usually increasing with LAI. This is because a higher LAI (or EVI) leads to an increase in T. In addition, it also reduces E due to radiation shading and wind sheltering. However, given that T:ET is also dependent on solar radiation and VPD, the covariation of these variables with EVI within a season can alter the T:ET-EVI relation. Modification of EVI due to grazing during the growing season significantly alters the covariation of EVI and VPD or EVI and radiation, thus degrading the strength of T:ET-EVI relation. In fact, for many undisturbed sites, temporal variations of solar radiation, VPD, and/or soil moisture may lead to a weak T:ET-EVI relation.

4. Conclusions

Using T:ET-EVI relations, ET partitioning was performed in winter wheat systems with varied grazing management schemes. Comparison with partitioning estimates obtained based on three ET partitioning methods, viz. FVS theory, uWUE, and TEA, all indicate a robust T:ET-EVI relation in a standard undisturbed system. In contrast, the relation in disturbed systems, realized by cattle grazing in this case, is weak and does not capture the data variance well. The results indicate that the relation between vegetation indices and T:ET is affected by canopy alterations, which in this study was due to grazing management but could also be a result of other natural (e.g., fire or drought) or anthropogenic (e.g., thinning) disturbances. In addition, our results show prediction of T:ET at weekly to monthly scale using the T:ET-EVI relation of undisturbed systems in disturbed system introduces large errors. As prediction of T:ET using data from disturbed system in an undisturbed system and vice-versa introduces uncertainty in T:ET estimates, the results point to limited translatability of the method across systems. Given that more than 40% of the global land is managed or disturbed (Ellis et al., 2010), the results underscore the need for caution while assessing ET partitioning using vegetation indices over managed or disturbed systems. This is also relevant as many remote-sensing and land surface models formulate T:ET as a function of these plant development metrics (Lian et al., 2018; Miralles et al., 2016; Talsma et al., 2018). Notably, the impact of grazing management on T:ET estimate at the seasonal scale is negligible. This is attributable to plants' adaptation to the given water resources and the compensatory effects of E from wet canopies and wet soil surfaces under contrasting (dense and sparse) canopies.

Investigation on the possible causes of the altered T:ET-EVI relation suggests that grazing disturbed the co-variation of EVI and VPD (and of EVI and solar radiation), resulting in divergence from the standard T:ET-EVI relation. As the covariation between VPD (or solar radiation) and EVI can be easily evaluated using global meteorological forcings (Mooney et al., 2011; Warszawski et al., 2014; Weedon et al., 2014; Xia et al., 2012) and vegetation (Benedetti & Rossini, 1993; Hatfield & Prueger, 2010; Huete et al., 1994, 2002; Jiang et al., 2008; Nguyen et al., 2020; Rocha & Shaver, 2009) data, future studies may use this metric, after further assessments in alternative settings, to map regions where vegetation indices are likely to be effective for ET partitioning.

Data Availability Statement

Authors thank developers of the Fluxpart source code, which is accessible at https://github.com/usda-ars-ussl/fluxpart (accessed on 10 November 2020). The code for TEA algorithm is available at https://doi.org/10.5281/zenodo.3921923. The code for uWUE algorithm is available at https://github.com/praghav444/WaterFlux-Partitioning. Data for this work are publicly available (Raghav et al., 2022, https://doi.org/10.15482/USDA.ADC/1527834)

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