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RESEARCH PAPER

Attributing Vegetation Recovery During the Indian Summer Monsoon to Climate Drivers in Central India

Vikram Chandel* and Tejasvi Chauhan**

Abstract: Increasing droughts and heat waves as a result of global warming pose a major threat to forests and croplands in India. Monitoring the dynamics of vegetation during a drought and its recovery is essential for the Indian socio-economy and biodiversity. We investigate vegetation recovery from a stressed state in the pre-monsoon (May) period to the end of the monsoon period (September). We then attribute net change during the monsoon period to climate drivers such as temperature, precipitation, and soil moisture. To delineate non-linear interactions, we use an information-theoretic metric to understand the relative association of climate variables with vegetation productivity on a daily scale. We found that pre-monsoon vegetation stress is influenced by soil moisture ($r = 0.8$, $p < 0.01$), which is driven by variations in temperature and precipitation. During the monsoons, precipitation contributes to vegetation recovery from pre-monsoon stress through soil moisture recharge while inhibiting vegetation productivity by limiting the amount of radiation available for photosynthesis. Linear regression shows the significant negative dependence of vegetation recovery on precipitation ($\beta = -0.7$, $p < 0.01$) and positive dependence on soil moisture ($\beta = 0.4$, $p < 0.1$) indicating radiation limitation on photosynthesis. We also found that post-monsoon vegetation recovery is independent of pre-monsoon vegetation stress ($p > 0.1$). Mutual information showed the stronger, non-linear dependence of vegetation recovery on soil moisture than on precipitation, which is a contrasting result that highlights the importance of including non-linear measures in analyses of natural systems. Our results show that vegetation recovery in central India is driven by soil moisture during the Indian summer monsoon and is independent of pre-monsoon vegetation stress.

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1. INTRODUCTION

The frequency, intensity, and spatial extent of droughts has been increasing in India due to global warming (Mishra, Shah, and Thrasher 2014; Gupta and Jain 2018). Droughts are often accompanied by heat waves, leading to increased mortality due to heat stress (Rohini, Rajeevan, and Srivastava 2016; Panda, AghaKouchak, and Ambast 2017; Mazdiyasni *et al.* 2017). Apart from affecting human life, droughts adversely affect vegetation by changing carbon fluxes, causing soil water storages, and disrupting ecosystem services. Consequently, food production (Zhang *et al.* 2017) in the country is threatened. Prolonged droughts can lead to irreversible shifts in vegetation phenology, thus threatening the biodiversity of a region (Clark *et al.* 2016; Wendling *et al.* 2019).

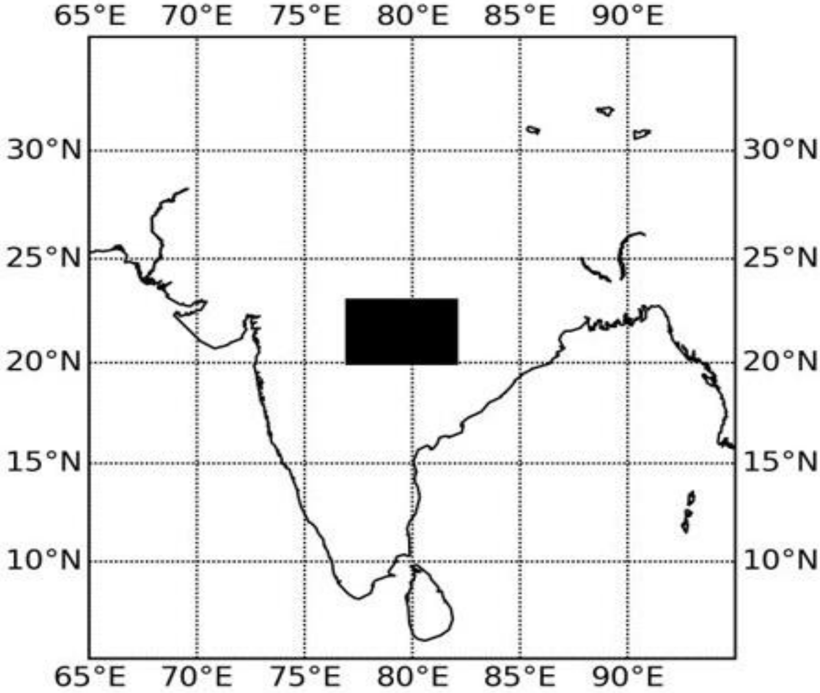
Vegetation responds to drought conditions at varying time scales depending on its physiology, and this response that vegetation has to any stressor can be quantified using different metrics (Vicente-Serrano *et al.* 2013). Resilience is defined as the ability of a system to return to its original state after a disturbance (Scheffer *et al.* 2009). Resilience can be measured as the time taken by a system to return to its original state after a disturbance. Resistance is defined as the ability to persist and resist change during a disturbance (Nimmo *et al.* 2015). It can be quantified as the deviation of processes and variables from the mean state during a disturbance; the more the deviation, the less the resistance. Recovery is the process by which an ecosystem retreats toward the pre-disturbance state (Fraccascia, Giannoccaro, and Albino 2018). These metrics help us study the response of different vegetation ecosystems ranging from croplands to tropical rainforests.

Forests serve as carbon sinks in the global carbon cycle (Soepadmo 1993; Whitehead 2011; Martin *et al.* 2001). Understanding the response of forests to drought is important for understanding carbon cycles and any potential adversities to biodiversity. Drought and heat stress cause large-scale tree mortality, which affects the forest phenology and the carbon cycle and turns forests into carbon sources (Ciais *et al.* 2005; Anderegg, Kane, and Anderegg 2013; Ma *et al.* 2016; 2015, Li *et al.* 2019; Jiao *et al.* 2020; Schuldt *et al.* 2020; Senf *et al.* 2020).

The drivers of recovery in a forested ecosystem are climate variables, forest type, and forest stock volumes (Anderson-Teixeira *et al.* 2013, Luo *et al.* 2022). An ecosystem requires an optimum amount of soil moisture, soil nutrients, air temperature, and solar radiation for a speedy recovery. Soil moisture is recharged by precipitation and depleted by evapotranspiration driven by the air temperature and vapour pressure deficit in the atmosphere. The optimum temperature for photosynthesis in an ecosystem depends on the biodiversity of the ecosystem (Bonan 2015). Sunlight is an essential ingredient in the process of photosynthesis, and cloudy days result in a decline in photosynthetic rates due to a lack of direct solar radiation. Here, we focus on the interplay of climate variables such as soil moisture, temperature, and precipitation in driving vegetation recovery.

We use the leaf area index (LAI), to measure the state of vegetation. LAI is defined as the one-sided green leaf area per unit ground area in broadleaf forests and as half the total needle surface area per unit ground area in coniferous forests. The recovery rate of vegetation system can be measured by the rate of photosynthesis. Gross primary productivity (GPP), a proxy for the photosynthetic rate, is the amount of chemical energy produced by primary producers during photosynthesis. We use both LAI and GPP to study vegetation recovery and its climate drivers in a forested ecosystem.

Figure 1: Study Region Lies in Central India, Bounded by 20°N, 77°E, 23°N, and 82°E



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We selected a biodiversity-rich forested region in central India (Figure 1a), bounded by 20°N, 77°E, 23°N and 82°E. The region encompasses the Melghat Tiger Reserve, Satpura National Park, Pench National Park, and some agricultural areas. We investigate the ecosystem's recovery from a stressed state in the pre-monsoon (May) period to the end of the monsoon period (September). We analyse deviations in the vegetation amount during the pre-monsoon and post-monsoon periods and attribute the net change during the monsoon period to climate drivers such as temperature, precipitation, and soil moisture. We also examined the dependence of post-monsoon vegetation stress to pre-monsoon vegetation stress. To delineate non-linear interactions, we use an information-theoretic metric to understand the relative association of climate variables with vegetation productivity on a daily scale.

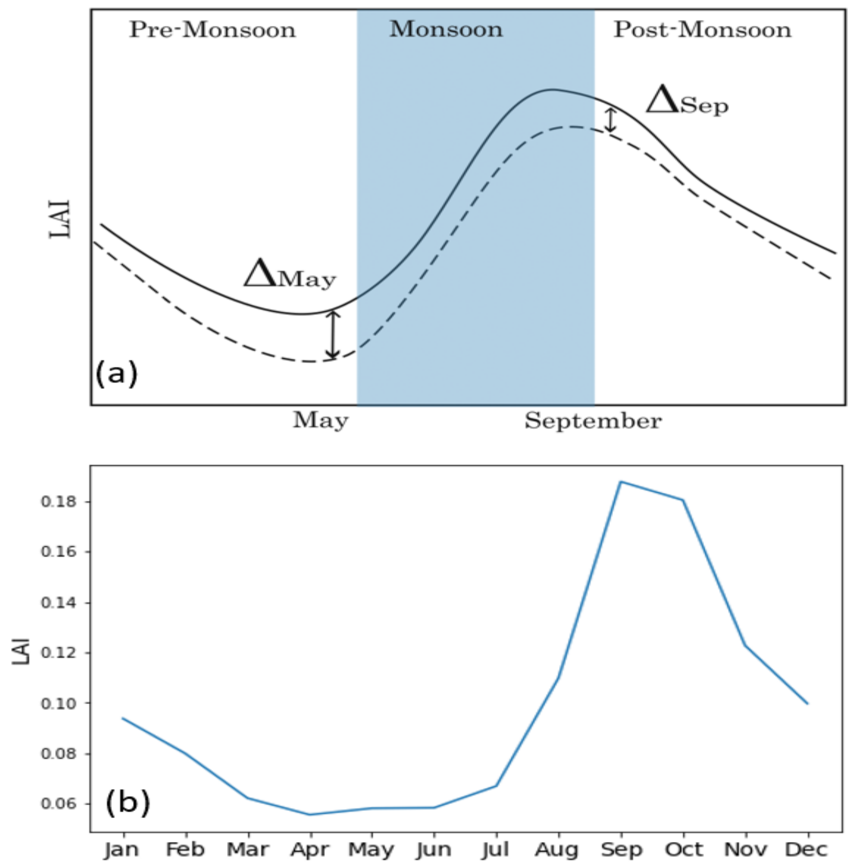
2. DATA AND METHODS

We use the leaf area index (LAI) obtained from the moderate resolution imaging spectroradiometer (MODIS). This product has a spatial resolution of 500 m and a temporal resolution of eight days. We used rainfall (P) (Pai *et al.* 2014) and temperature (T) gridded data from the Indian Meteorological Department (IMD). We used the Global Land Evaporation Amsterdam Model (GLEAM V3) dataset to determine soil moisture (SM) (Martens *et al.* 2017). We also used daily gross primary productivity (GPP) data from FluxSat v2.0, which is a combined dataset of the FLUXNET eddy covariance tower site data and satellite data from MODIS (Joiner and Yoshida 2020).

2.1 VEGETATION STRESS

We use percent anomaly in the month of May (Δ_{may}) as an indicator of stress in vegetation. We look at the percent anomaly after the monsoons and calculate the Δ_{sep} for September. Both Δ_{may} and Δ_{sep} (Figure 2) can take positive and negative values. We use May and September, as during the monsoon period, satellite products like LAI are unreliable due to frequent cloud cover.

Figure 2: (a) Schematic Diagram Representing Vegetation Anomalies Proposed for Measuring Vegetation Recovery; (b) Climatology of the Leaf Area Index (LAI) over the Study Region



Source: Authors' analysis

2.2 INFORMATION THEORY

Uncertainty (or variability) of a time series $X_t = \{x_1, x_2, x_3, \ldots, x_t\}$ which can be classified into 'm' different states can be quantified using Shannon's entropy as

$$H(X_t) = \sum_{i=1}^{m} p_i(x_t)(\log(p_i(x_t))) \quad (1)$$

where $p_i(x_t)$ is the probability (or relative frequency) of the i^{th} state and H is bound as $0 \leq H \leq \log(m)$. H can be normalized using $\log(m)$ to form H_{norm}. In dynamical systems, in any interaction between two variables X_t and Y_t uncertainty regarding one variable reduces when we have information about another. This reduction in uncertainty is called Mutual Information (MI) and can be computed as

$$MI(X_t, Y_t) = H(X_t) + H(Y_t) - H(X_t, Y_t) \qquad (2)$$

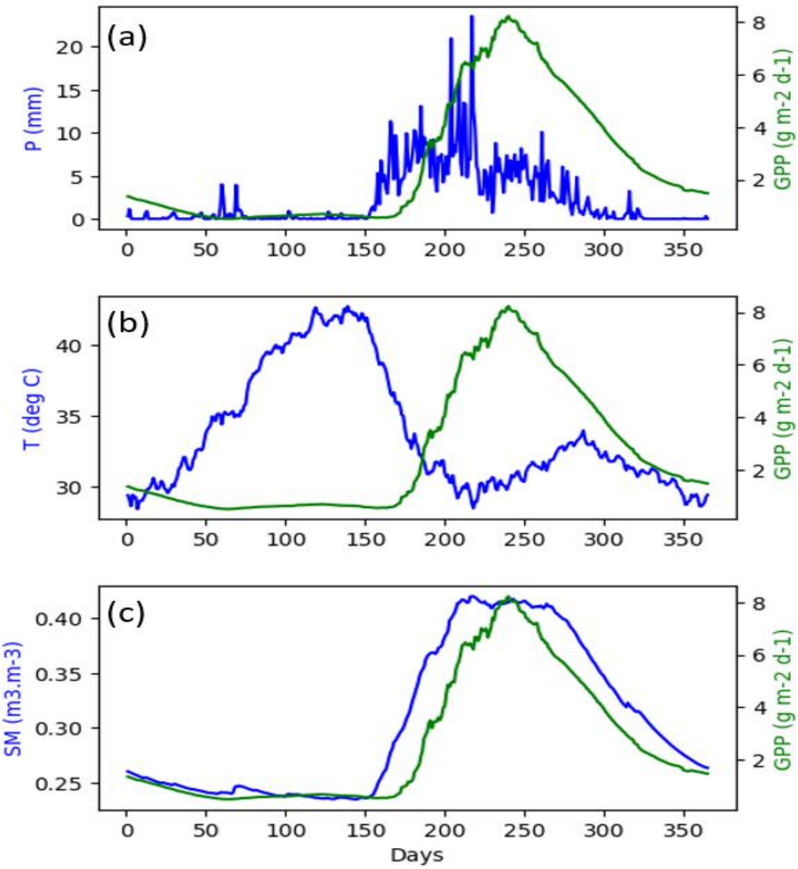
Where $H(X_t, Y_t)$ is the joint entropy computed using the joint probabilities of X and Y in equation 1 or 2. MI is bound as $0 \leq MI(X_t, Y_t) \leq \min\{H(X_t), H(Y_t)\}$. It can measure non-linear associations between variables and hence has been argued to be a measure of true statistical independence (Knuth *et al.* 2013). To compare the associations between various components inside a system, MI can be normalized as $MI_{norm} = MI/\min\{H(X_t), H(Y_t)\}$ which indicates the percentage of variance of one variable that be explained using another.

In this work, to compare the linear and non-linear dependencies of vegetation on precipitation, soil moisture, and temperature, we compute pairwise normalized mutual information (MI_{norm}) of daily datasets of soil moisture (SM), temperature (T), and precipitation (P) with gross primary productivity (GPP) to understand the association of hydrometeorological variables with vegetation productivity for the various above-discussed transitions of vegetation stress from May to September for our study region. We partition each time series into 11 bins and compute pairwise MI_{norm} using Equation 3 for each year separately and then compute the average MI_{norm} for the years falling in the above-discussed transition types.

3. RESULTS

Figure 3 shows the climatology of precipitation (P), temperature (T), soil moisture (SM), and gross primary productivity (GPP) in the study area in central India (figure 1). Central India receives rainfall during the Indian summer monsoons (ISMR) in June–September (JJAS). The pre-monsoon period sees high temperatures along with minimal rainfall, while the onset of ISMR provides respite from the heat of summer. The region experiences temperatures as high as 40°C during April and May, which reduce on the arrival of the monsoons and vary from 30–35°C during and after the monsoons. GPP (Figure 3), a measure of photosynthesis, remains low in the pre-monsoon period due to the unavailability of soil moisture and rises with an increase in soil moisture after the onset of the monsoons. Since GPP is influenced by the air temperature and the amount of radiation and moisture available, if the condition of air temperature and radiation is fulfilled, it is mainly driven by water availability. We observe similar behavior in our region as the seasonal variation of GPP is similar to variation in SM.

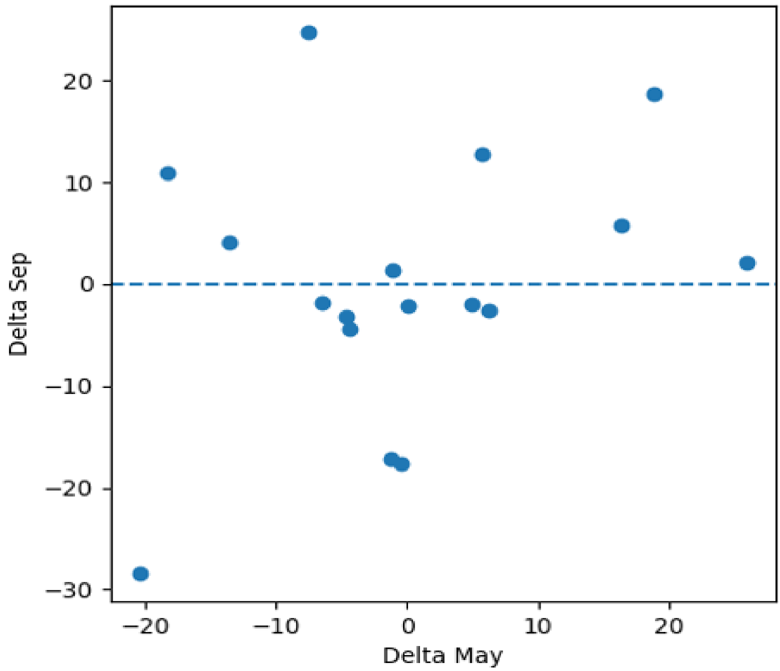
Figure 3: The Climatology of Precipitation, Temperature, and Soil Moisture and Gross Primary Productivity



Source: Authors

To understand the recovery of our system, we see the magnitude of stress in vegetation in different years (Figure 4). The negative values of percent anomaly (Δ) indicate stress in vegetation. Δ_{may} varies from -20% to 25%. We performed Pearson correlation of Δ_{may} with precipitation, temperature and soil moisture during the pre-monsoon period of March, April and May. We found that temperature has a correlation of –0.7 ($p<0.01$) which signifies that hotter pre-monsoon period puts stress on vegetation. We found positive correlation of delta with soil-moisture (0.80; $p<0.01$) and precipitation (0.62; $p<0.01$), which implies that these variables reduce the stress in month of May.

Figure 4: Scatter plot of percentage anomaly in May LAI (Δ_{may}) and corresponding change in September (Δ_{sep}) in same year



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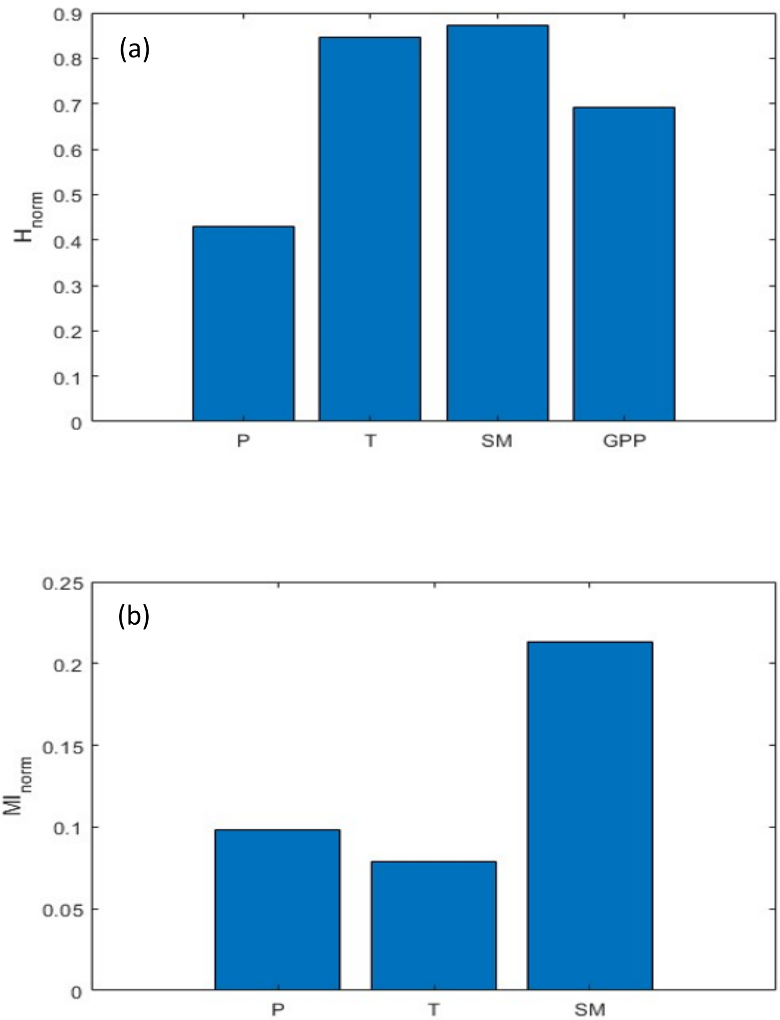
Δ_{sep} varies from –30% to 25% across the years (figure 4). To understand the dominant hydro-meteorological drivers of vegetation productivity during monsoon, we performed a linear regression of Δ_{sep} with cumulative precipitation anomalies, mean temperature anomaly, and mean soil moisture anomaly during JJAS. We found that Δ_{sep} has a significant (p-value < 0.05) association with soil moisture and precipitation with coefficients –10.1 and 6.2 respectively. Negative coefficient between P and GPP is counter-intuitive and indicates a reduction in vegetation productivity due to radiation limitation imposed on photosynthesis by cloud cover. Hence, high (and continuous) precipitation can lead to a loss of vegetation productivity. SM on the other hand has a positive coefficient with GPP as soil moisture recharged by precipitation takes time to deplete and can aid photosynthesis when solar radiation is available.

The negative anomaly in September is present for both positive and negative values of Δ_{may} (Figure 4). This demands further investigation to find out whether Δ_{sep} depends on Δ_{may} or not. To investigate, we added Δ_{may} as an additional predictor to the above regression. We did not find any statistically significant coefficient for Δ_{may} and there was no change in the coefficients of climate other variables. This shows that variations in Δ_{sep} are insensitive to variations in Δ_{may} . Since linear regression fails to capture non-linear associations, we employ information-theory based metrics to capture the non-linearities.

Figure 5(a) shows average normalised Shannon's entropy of P, T, SM, and GPP across all years. Shannon's entropy quantifies the variability of a time series. P and SM are the variables with the lowest and highest entropies, respectively, with the entropy of P at around 40% and that of SM at 90% of the maximum possible value of log(m). Entropies of T is slightly lesser than SM with values between 80%–90% of H_{max}. Entropy of GPP is between 60%–70% of H_{max}. While Shannon's entropy measures the variability, mutual information (MI) measures the amount of variability that can be explained between any two variables in the system. MI measures non-linear associations as well, and, hence, is a better measure of association between any two variables. To understand the dynamic association of hydrometeorological variables with GPP, we computed mutual information between these variables. Figure 5(b) shows the average normalised mutual information (MI_{norm}) of P, T, and SM, with GPP, where MI_{norm} is ratio of MI to maximum MI to enable comparison across multiple variable pairs (See methods). MI_{norm} indicates the percentage variance of a variable that can be explained by another variable.

SM has highest MI with GPP, varying from 20% to 25%, showing the strong association between variability in soil moisture and variability of vegetation productivity in the region. While linear regression showed the almost equal (and opposite) strength of association between GPP and P and SM, MI shows that GPP has a stronger association with SM—the association is almost twice as strong as than with P. Different relative strengths of association across linear regression and MI indicate strong non-linear associations that linear regression fails to capture. The extra strength of the association between SM and GPP, hence, comes from non-linear interactions. The overall positive association between SM and GPP offsets the negative coefficient of P seen in the linear regression and hence leads to positive vegetation productivity. This shows that for our study region, recovery of vegetation from stressed pre-monsoon conditions has a strong dependence on soil moisture.

Figure 5: (a) Average Normalised Shannon's Entropy of P, T, SM, and GPP across All Years; (b) Average Normalised Mutual Information (MI_{norm}) of P, T, and SM, with GPP Where MI_{norm} Is the Ratio of MI to the Maximum MI to Make It Useful for Comparison across Multiple Variable Pairs



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While our study provides novel insights on the vegetation dynamics of forest regions, it ignores agricultural areas that are heavily affected by human interventions such as irrigation. Dynamics of vegetation may differ in the presence of anthropogenic stresses, which needs further examination. The independence of September vegetation from May vegetation may not hold for extreme events such as forest fires, heatwaves, and prolonged droughts. During such events, vegetation may cross a tipping point and experience irreversible changes. Precipitation shows a negative correlation with vegetation productivity, which is counter-intuitive. Since precipitation in our study also acts as a proxy for solar radiation, including data such as photosynthetically active radiation (PAR) will provide more accurate inferences.

4. CONCLUSIONS

Our study tries to measure the recovery of vegetation from pre-monsoon stress between the months of May and September using deviations from climatology. Since good quality observed datasets are not available for the monsoon period, our approach is a novel method to characterise vegetation recovery and attribute it to climate variables using datasets for the months of May and September, which are mostly available. We tried to attribute vegetation stress to climate variables and found that pre-monsoon monsoon vegetation stress depends on soil moisture, which is driven by variations in temperature and precipitation. Since pre-monsoon precipitation is sparse, heat waves during the pre-monsoon period can deplete soil moisture rapidly. During the monsoons, precipitation contributes to vegetation recovery from pre-monsoon stress through soil moisture recharge, while it also inhibits vegetation productivity by limiting the available radiation for photosynthesis. While linear methods show the strong negative dependence of vegetation on precipitation, indicating radiation-limited photosynthesis, metrics that include non-linear dependencies such as mutual information show stronger dependence on soil moisture. These contrasting results highlight the importance of including non-linear measures in analysis of natural systems.

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