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Disentangling Forest Dynamics for Litter Biomass Production in a Biosphere Reserve in Central India

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Investments in energy sources are scaling up across India to improve climate security and further mitigate future climate change. Forest biomass and litterfall pattern play an important role in the sustainable management of forests and the efficient utilization of resources. This study investigates the seasonal litterfall biomass pattern for five consecutive years (2015–2019) in four different vegetation types in Central India (AABR) using the litter traps method on the forest floor. An ANOVA model was adopted to infer the effects of forest types, litter types, and seasonality on litterfall production. The estimated mean litterfall of the dry tropical forest in Central India was recorded as 4.19 ± 0.305 Mg/ha/y where teak plantations contribute higher values compared to other studied vegetation types. A positive correlation was observed between the litterfall and nutrient storage with soil-adjusted vegetation index and other vegetation indices. The findings of litterfall pattern and turnover rate of nutrients indicated that the vegetation types of AABR have huge potential for carbon sequestration and help to achieve the Conference of the Parties (COP-26) goal of reducing regional and/or global climate change.

Keywords: litterfall biomass, landscape ecology, plant climate interation, climatic variables, carbon sequestration

INTRODUCTION

Forest litter biomass is one of the key biological resources of natural systems that provides various ecological services and is an important area for sustainable bio-economy as a way of facing the challenges associated with global climate change (Thakur et al., 2021; Sun et al., 2022). The substitution of biomass for fossil fuels in energy consumption is a key measure to reduce the atmospheric greenhouse gas (GHG), which mitigates global warming (Kumar et al., 2021a). In this perspective, proper utilization of forest biomass for energy production is generally acknowledged and is considered helpful for achieving sustainable development goals (Kumar et al., 2021b). Global warming, which is a result of growing levels of carbon dioxide (CO_2) in the Earth's atmosphere, is directly linked to sustainability in the period of climate change and must be addressed for stabilization. In the recent past, the atmospheric CO_2 level has reached

418.81 ppm (NOAA-ESRL, 2021), which could, in turn, increase the rate of photosynthesis resulting in a further increase in vegetation productivity. Tropical forests of India play a significant role in carbon sequestration, which is mostly stored in above-ground biomass and litterfall (Thakur et al., 2021). In the terrestrial ecosystem, vegetation and its underlying soil may store a significant quantity of carbon. Climate change has increasingly gained global momentum as a major threat to the survival of humankind and other living beings. Reducing CO_2 levels in the atmosphere and its accretion in plant biomass is one of the viable means of mitigating climate change (Sarto et al., 2020). It is an established understanding that the 26th Conference of Parties (CoP26) at Glasgow Climate Pact in 2021 has focused on action-oriented delivery on combating global climate change. Tropical Forests are considered the lungs of the world, yet, understanding and establishing sustainability in the bio-economy of these forests is the need of the hour (U-Din et al., 2022). India committed to having a "net zero" carbon emitter by 2070, where these tropical forests are good reservoirs of carbon both above-and-below ground (Kumar et al., 2021b). The present study is an attempt in this direction employing studying litterfall and litter dynamics linking to carbon sequestration and future energy security.

Litterfall is an important pathway for the return of organic matter (OM) and nutrients from above-ground biomass (AGB) to the forest floor, which is directly linked to the soil C pool (Wang et al., 2016). Soil organic carbon depends on the quantity of litterfall and the rate of its decomposition (Oelbermann et al., 2004). The litter dynamics tend to influence the leaf area index (LAI) and also the forest respiration rate, both of which are used as markers of change in carbon flux in the forest ecosystems (Joshi and Garkoti, 2020). Litter crop and productivity are unequivocally related to soil respiration or CO_2 efflux, which are strongly influenced by the factors like soil temperature, rainfall, and litter quality (Bond-Lamberty and Thomson, 2010). Understanding the C balance vis-a-vis nutrient transfer in terrestrial ecosystems, the estimation of litterfall is a prerequisite to measuring the patterns of soil C accumulation (Jia et al., 2020). Over the last few decades, there has been a rapid intrigue in the study of litterfall dynamics on various spatial scales (Souza et al., 2019) for numerous functions, i.e., to quantify nutrient dynamics (Zhu et al., 2019), energy security (Manolis et al., 2019), carbon and nutrient input (Feng et al., 2019), its contribution to net primary productivity (Chen et al., 2017), and in forest restoration (Lanuza et al., 2018). Various studies have been conducted on the litterfall dynamics in tropical forests, primarily in moist forests, with relatively few in dry tropical forests (TDFs) (Morffi-Mestre et al., 2020).

Often, TDFs are recognized as the largest major biomes in the world (Santos et al., 2012). Peak litterfall in TDFs usually occurs in the dry season to evade water losses through transpiration and endure vegetation under the conditions of stress and high vapor-pressure deficit (Aryal et al., 2015). At spatial scales (regional or worldwide), AGB and litter decay rates in TDFs will enhance with an increase in mean annual precipitation (Souza et al., 2019). Few studies reported that litter mass production synchronizes with canopy processes linked to phenology, vegetative, and reproductive growth phases and biomass production (Zeilhofer et al., 2012). The quantification of the litter production at higher temporal and spatial scales is cumbersome and restricts the development of the linkage between litter crop and complex canopy processes (Wang et al., 2016). Based on the existing literature, climatic variables (temperature and precipitation) and stand characteristics (vegetation type, canopy density, age, site quality, climate, and phenology) are some of the important elements that influence litterfall (Qin et al., 2022). The tropical forest provides many environmental services that are helpful, like biodiversity conservation, natural resource conservation and management, soil enrichment, temperature regulation, soil moisture conservation, etc., which subsequently reinstates the environment. The productivity and nutrient status of the soil is governed by the flow of a large number of inputs to the system (Jeet et al., 2014).

The geospatial techniques are quite indispensable for estimating canopy and stand characteristics, phenological changes, and associated processes in forest ecosystems (Liu et al., 2021). Greenness and phonological variations of vegetation could be easily detected from time-series data of normalized difference vegetation index (NDVI) derived from satellite images. This data could serve as a proxy for precisely enumerating the vegetation changes and biomass productivity of different settings (Frolking et al., 2009). Remote sensing indices such as enhanced vegetation index, photosynthetic vegetation, and photochemical reflectance index proved to be convenient predictors related to vegetation phenology and stand characteristics (Wang et al., 2020; Khan et al., 2022).

The litterfall in TDFs is strongly correlated with annual, seasonal, and monthly precipitation, temperature, and soil fertility (Morffi-Mestre et al., 2020). Long-term studies have proven to be effective in estimating litter mass production in TDF, which is regulated through cycles of precipitation and temperature (Tang et al., 2010). Aryal et al. (2015) detected one or more irregular peaks of litterfall measured at monthly intervals in different periods of the year. The seasonal and inter-annual patterning of litterfall accumulation has also been studied to quantify the effects of the litter dynamics on carbon and nutrient cycling (Chave et al., 2010). Long-term studies on periodical variations in litterfall are vital in terms of forest ecosystem service assessment and ecosystem functioning to ensure the benefits of biodiversity, soil water conservation, hydrology, biomass, and energy supplies to societies (Shen et al., 2019).

The Achanakmaar Amarkantak Biosphere Reserve (AABR) in Central India is the 14th biosphere reserve of India declared in 2005 (Roychoudhury et al., 2019), and UNESCO recognized it as the world's heritage site in 2012 (Thakur et al., 2020). To date, studies carried out in AABR mainly focused on floristic composition (Thakur et al., 2019) to understand the traditional use of plants (Thakur et al., 2017) and the structure of understorey vegetation (Thakur et al., 2014). Few studies focused on assessing the effect of fireplace frequency (Kittur et al., 2014), land use and land cover change detection (Thakur et al., 2019), and the litterfall pattern in ABBR (Yadav et al.,

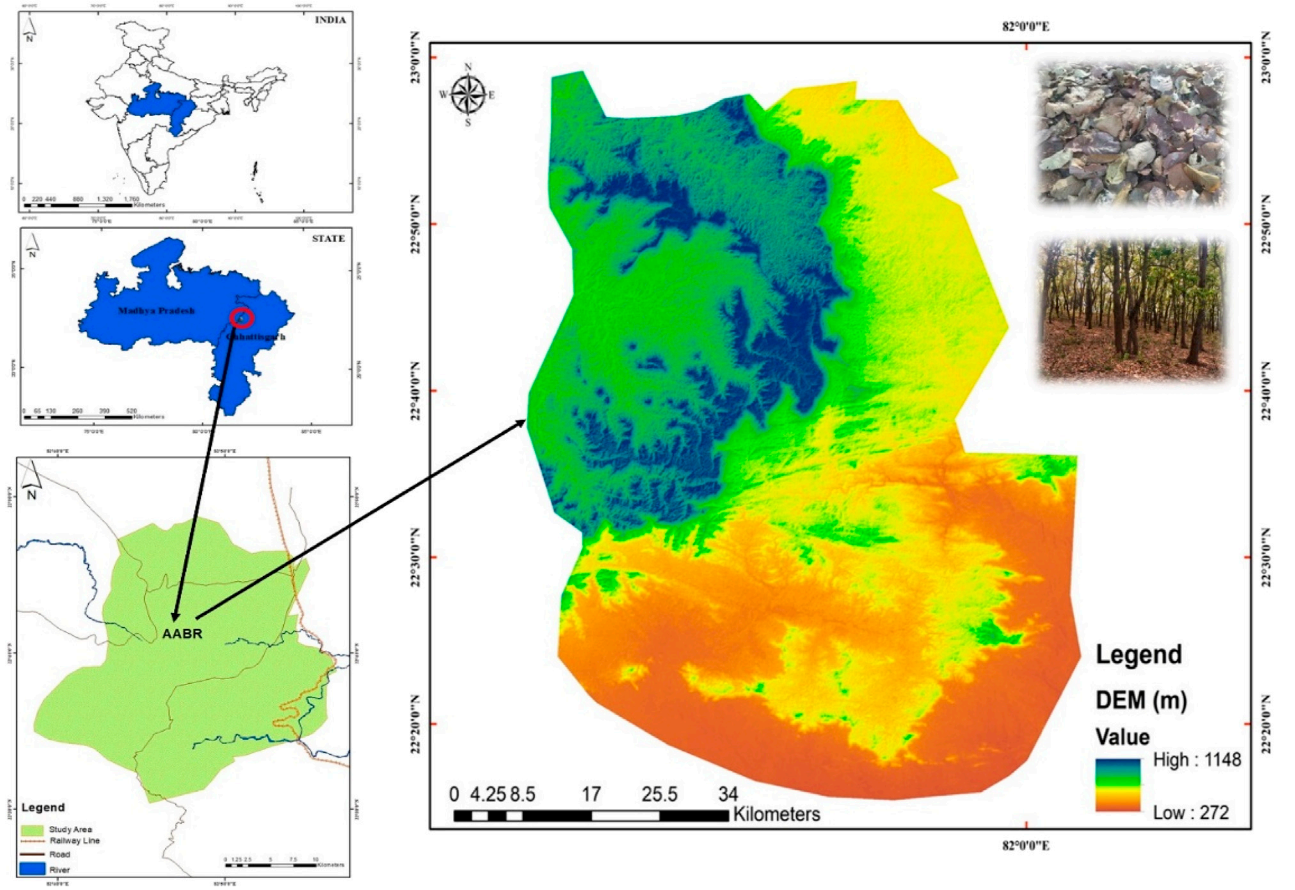

FIGURE 1 | Location Map (left side) and digital elevation model (DEM) (right side) of the study area.

2019). The results derived from the preliminary studies in AABR revealed that a maximum litterfall pattern was observed in the winter season, followed by the summer and the rainy seasons (Yadav et al., 2019). Darro et al. (2020) revealed that temporal studies are essential to understanding patterns of litterfall and soil organic matter (SOM) production in different vegetation types. The present study was conducted to analyze the litterfall pattern and macro-nutrient accumulation over 5-year period in four different vegetation types from the TDFs of AABR through remote sensing techniques with ground truth observations. This study aims to estimate and highlight the litterfall biomass production in the biosphere reserve in Central India for carbon neutrality. The objective of the study is 1) to quantify the seasonal patterns of litterfall using litter trap data of four different vegetation types, 2) to understand the influence of temperature and precipitation on litterfall, and 3) to examine the correlations among spectral vegetation indices with litterfall, carbon and nitrogen storage of the selected vegetation types of AABR. The studies will help in evolving site-specific forest management strategies for improving carbon storage and offsetting emissions to mitigate climate change for sustainable and efficient resource application.

MATERIAL AND METHODS

Study Site

The study was carried out in the TDF of AABR, which falls under the Deccan Peninsular zone as per the bio-geographic classification of India. It lies between the parallel of latitude 22°15′ to 20°58′N and longitude 81°25′ to 82°5′E. The AABR is covered by 3835.51 km^2, and 16% is under the seasonal dry tropical forest region. The location map, along with the digital elevation model (DEM) of the site and select sampling units, is depicted in **Figure 1**. The climate of the region is sub-humid tropical with summer, winter, and rainy seasons. In AABR, maximum precipitation (>80%) occurs from July to October in the rainy season. Winter starts in November and lasts until February, and summer from March to June. The rainfall varies from 1,050–1,500 mm/y, and the annual temperature is from 25.8 to 30°C at elevations of 884 m mean above sea level (m a.s.l). The average annual temperature (°C) and precipitation (mm) were 26.68°C and 1,197.23 mm. The mean annual temperature was maximum in 2017 (35.23°C) and minimum in 2015 (24.12°C) (**Figure 2I**), whereas the annual precipitation was high in 2016 (1,327.68 mm) and low in 2018 (1074.24 mm) (**Figure 2II**). Based on vegetation composition, the four different functional types,

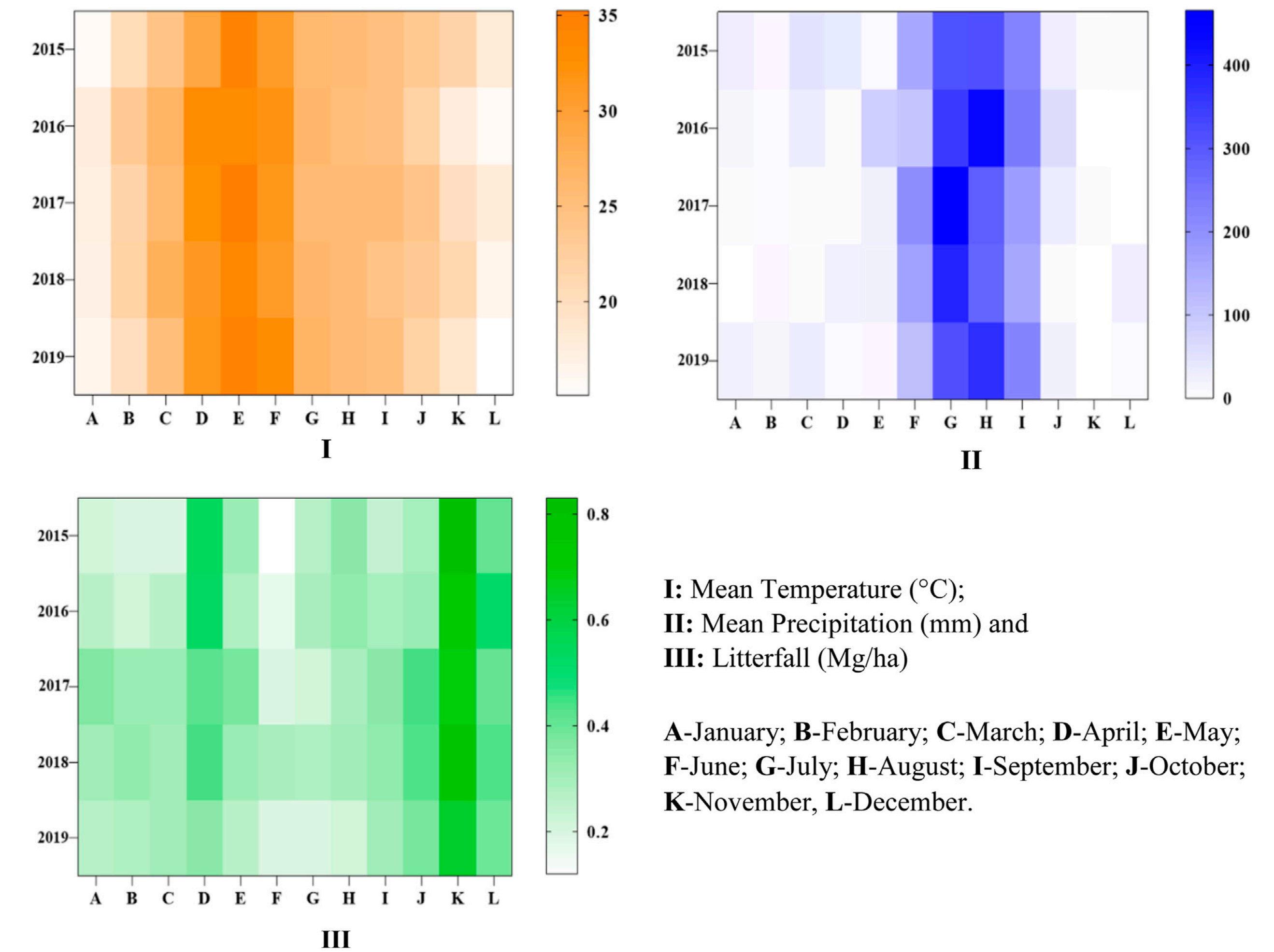

FIGURE 2 | Monthly estimation of various parameters recorded in AABR for the period 2015–2019. **(I)**: mean temperature (°C); **(II)**: mean precipitation (mm), and **(III)**: litterfall (Mg/ha). **A**-January; **B**-February; **C**-March; **D**-April; **E**-May; **F**-June; **G**-July; **H**-August; **I**-September; **J**-October; **K**-November, **L**-December.

i.e., teak plantations (TP), sal mixed forest (SMF), dense mixed forest (DMF), and open mixed forest (OMF) were identified in TDF. The field study sites of the selected vegetation types are shown in **Supplementary Figure S1**.

Structural Attributes and Soil Characteristics of TDFs

The stand characteristics were measured in permanent plots marked for long-term ecological research in different functional types of TDFs in AABR. The structural attributes of vegetation, such as stand density, basal area, crop height, canopy cover, canopy density, LAI, etc., were measured in these plots during 2015–2019 (Sagar et al., 2003). The structural attributes (altitude, slope, and plot area); biometric measurements of tree species (height, DBH, and basal area); density of trees (trees/ha), LAI (i.e., it is defined as the projected area of leaves over a unit of land (m^2 m^{-2}), so one unit of LAI is equivalent to 10,000 m^2 of leaf area per hectare), canopy parameters (canopy cover and canopy height) and soil characteristics (pH, texture, bulk density, soil OM and total nitrogen) were derived for all the selected forest types (DMF, SMF, OMF, and TP) as shown in **Supplementary Table S2**. The plot remains constant for all the vegetation types, i.e., 0.8 ha. The altitude (m a.s.l) and the slope (m) range from 505 to 720 m a.s.l and 35%–75%, respectively. The total number of trees present in the four vegetation types was 171, where DMF 52) recorded the most and TP 24) least. The number of trees in SMF and OMF was 49 and 46. The density of trees (trees/ha) was found to be maximum in the SMF region (652.5) followed by DMF (587.5), OMF (467.5), and TP (470). In terms of biometric measurements of the tree species associated with the vegetation types, the mean DBH (cm) ranged from 20 to 30 cm in TP and OMF; 25–35 cm in DMF, and 30–40 cm in SMF. The tree species present in SMF had higher values of height (m) and basal area (m/ha) and least in OMF, whereas, in DMF and TP, the values were almost similar (**Table 1**). A pH was relatively the same in SMF and DMF, ranging from 7–7.5, whereas, in the sites of OP and TP, it was slightly on the lower side ranging from 6–6.5. The relative fractions of sand, silt, and clay in the soil were almost similar in SMF and DMF. The bulk density of soil (0–30 and 30–60 cm) of

TABLE 1 | Structural attributes and soil characteristics of the different forest types in AABR.

Parameter	Forest types			
	TP	SMF	DMF	OMF
Plot area (ha)	0.8	0.8	0.8	0.8
Altitude (m)	557.17	626.59	719.65	505.43
Slope (m)	357.16	147.61	192.63	78.91
Number of tree species	24	49	52	46
Density (trees/ha)	470	652.5	587.5	467.5
DBH (cm)	20–30	30–40	25–35	20–30
Height (m)	15	22	18	12
BA (m^2/ha)	28.81	34.12	29.05	9.26
Canopy height (m)	12.75	19.12	16.95	11.05
Canopy cover (%)	65	75	80	35
Leaf area index (m^2/m^2)	3.65	6.2	5.5	2.85
Soil pH (1:2.5 ratio)	6.5	7.1	7.3	6.3
Sand (%)	52.25	49	49.5	49.75
Silt (%)	30.5	32.25	33	35.5
Clay (%)	17.25	18.75	17.5	14.75
BD (g cc^{-3})	--	--	--	--
0–30 cm	1.4	1.41	1.43	1.49
30–60 cm	1.43	1.45	1.51	1.55
SOM (g/kg)	15.25	17.65	18.15	15.09
Total N (mg/ha)	2.2	2.5	2.35	1.82

soil depth was found to be higher in OMF and least TP. The SOM content was higher in DMF followed by SMF, TP, and OMF, while SMF showed a high N content, which was least under OMF (**Table 1**).

Estimation of Standing Litter

The standing litter crop was measured by using three sub-quadrates (0.5 m × 0.5 m) laid randomly on the forest floor in different sample plots (20 m × 20 m) distributed in four forest types. The standing litter was collected in 15 sample plots (3 locations within quadrate × 5 quadrates) from each forest, constituting a total of 60 plots laid in four vegetation types of dry tropical forests of AABR. The litter samples were collected in polyethylene bags at monthly intervals and were transported to the laboratory from 2015 to 2019. These collected samples were separated into different litter components such as leaves, wood, fruits, flower, and bark components. Litter fractions were dried at 80°C in a hot air oven for three days; thereafter, the samples were weighed using an analytical scale (0.0001g). The weights of the dried samples of the different litter components were taken, and the values were converted to Mg/ha. The litter components (leaves, wood, bark, and twigs) were added to derive the total standing litter. The average of all five years was considered to calculate the mean standing litter for a given functional type to calculate the turnover rates.

Along with standing litter, litterfall on the forest floor, i.e., litter input, was recorded in three different seasons (rainy, winter and summer) for each year using the above-described protocol (Zhu et al., 2021). The litterfall of three seasons was compiled and then added to obtain the total annual litterfall (Mg/ha). The total litterfall obtained from 2015–2019 was averaged to derive the mean annual litterfall of each forest type (Mg/ha/y).

Turnover of Litter and Sustainability

To realize sustainability, in the present study, we calculated the turnover rate of litterfall for the selected sites of AABR. The turnover rate (K) of the litter was calculated as described in Jenny et al. (1949).

$$K = \frac{A}{A + F} \tag{1}$$

where A = annual increment of litter and
F = amount of litter at a steady rate.

In this study, F is the lowest value of the standing litter in the annual cycle, while turnover time (t) is expressed as $t = 1/K$.

Physico-Chemical Analysis of Soils, Litter, and Meteorological Data

The physicochemical properties (pH, bulk density, texture, OM, C, total N) of soil (up to 10 cm) collected from four different types were determined in 2019. In a similar manner, the total organic carbon was estimated following the procedure by Walkley and Black (1934); (Kumar et al., 2021a), while total N was analyzed by adopting the micro-Kjeldahl method (Jackson, 1958). Monthly meteorological data (precipitation and mean temperature) was acquired from the Indian Meteorological Department, New Delhi, for the years 2015–2019.

Satellite Remote Sensing Data Predictors

Cloud-free satellite data of the study area for the years 2015–2019 was acquired freely from the United States Geological Survey website (GloVis, 2021), as shown in **Supplementary Figure S2**. All the electromagnetic wavelength/bands (Visible and NIR bands) were stacked and pre-processed in ERDAS Imagine (version 9.3); the geometric and atmospheric corrections were done before further analysis. The spectral vegetation indices derived from satellite data, maps of normalized vegetation moisture index (NDMI), NDVI, and oil-adjusted vegetation index (SAVI) were generated.

ANOVA Model for Variation in Sustainable litterfall Over Selected Forest Types, Litter Types, and Selected Reference Periods

The variation observed in the litterfall (LF) may be attributed to the differences in selected forest types (DMF, OMF, SMF, and TP), litter types (leaves, twigs, and wood), and selected reference periods (2015, 2016, 2017, 2018, and 2019). The variation of LF over selected forest types, litter types, and selected reference periods are modeled as a three-way repeated-measures ANOVA model given $F + L + P$ where LF denotes the litterfall (Mg/ha) and is considered as the dependent variable, F as forests, L as the litter type and P denotes the reference period.

Because of the non-normal distribution of LF, Box-Cox transformed values of LF (denoted as y) are utilized in the ANOVA model. The transformation is given as:

TABLE 2 | Linear regression models for $ln(LF)$ and predicting functions for.LF

Model no.	Model for $ln(LF)$	R^2	Predicting function for LF
M1	$\alpha\, ln(40+P)$+)dicting equation ϵ	0.92	$(40+P)^{-0.25}$)dicting equation
M2	$\beta T + \epsilon$	0.89	$e^{-0.04T}$
M3	$\gamma_1\, ln(0.18+P) + \gamma_2 T + \gamma_3 T\, ln(0.18+P) + \epsilon$	0.93	$(0.18+P)^{-0.26+0.007T} e^{-0.04T}$

$$y = \frac{(LF)^{0.25} - 1}{0.25} \tag{2}$$

The residuals of the ANOVA model are tested for normality using the Anderson–Darling test (p-value 0.38) (Stephens, 1974). Post-hoc tests were carried out to infer the differences in the amount of LF contributed by different categories of the three factors in the model.

Regression of Litterfall on Temperature and Precipitation

The data set contains monthly data on precipitation (P), temperature (T), and LF for five consecutive years from January 2015 to December 2019. The recorded T varies in the range from 15.07 to 35.03°C. The amount of P ranges from 0 to 465.74 mm where LF has the least value of 0.12 (Mg/ha) and a high of 0.83 (Mg/ha). The distribution of LF was found to be non-normal. LF is, log-transformed, and the distribution of ln (LF) was tested for normality using the Anderson–Darling normality test (p-value 0.08). The following statistical analyses utilize the transformed variable ln (LF).

Three different sets of linear regression models were considered for predicting ln (LF) with P as a predictor, T as a predictor, and T & P together as predictors. Among the set of models, the parsimonious models with a high value of R^2 are utilized for the present study (**Table 2**). Depending upon the model utilized LF can be predicted for a given P, T, or both P & T by utilizing the predicting functions given in **Table 2**. The models *M1*, *M2*, and *M3* predict mean LF for a given value of P, V, and P-V. To assess the performance of these models, the dataset was divided into four sub-datasets, namely S_1, S_2, S_3, and S_4. These sub-datasets represent different scenarios of P and T. The criteria for sub-datasets were based on median P (26.74 mm) and median T (25.06°C). The data points with precipitation below-median P are defined as points of low precipitation (LP), and the rest of the data points are defined as points of high precipitation (HP). The data points with temperature below-median T are defined as points of low temperature (LT), and the rest of the data points are defined as points of high temperature (HT). The two criteria are crossed to produce four sub-datasets, namely S_1 (LP–LT), S_2 (HP–LT), S_3 (HP–HT), and S_4 (LP–HT). The predicted LFs for the median temperature and mean rainfall for each sub-dataset are obtained using *M1*, *M2*, and *M3*. These predicted LFs are compared with the average (geometric mean) LFs for each sub-dataset. The data analysis was performed using statistical software R (version 3.6.3).

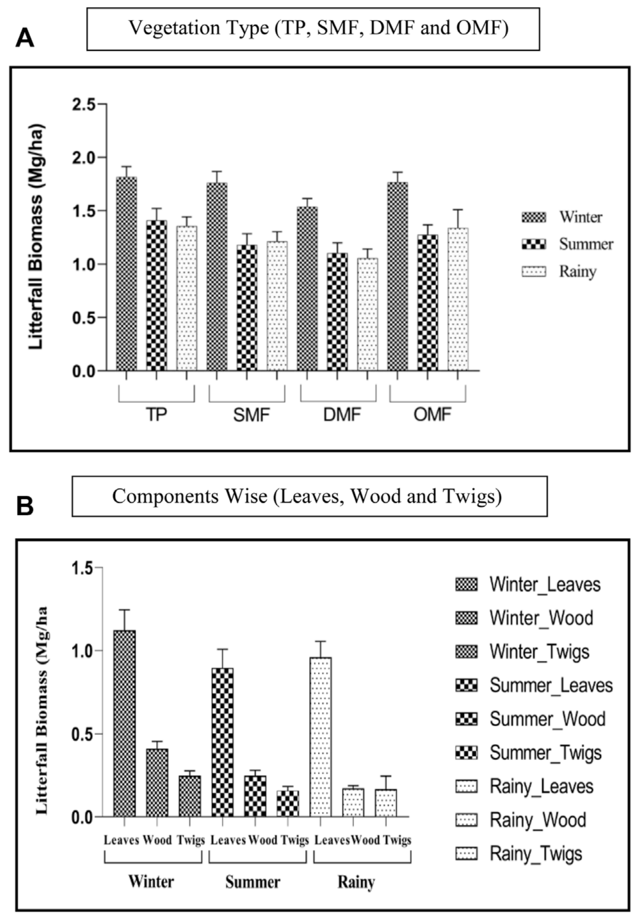

FIGURE 3 | Mean annual seasonal litterfall production in AABR for the period of 2015–2019. **(A)**: vegetation type (TP, SMF, DMF, and OMF). **(B)**: components wise (leaves, wood, and twigs)

Correlations Among Spectral Vegetation Indices (NDVI, SAVI, and NDMI), Sustainable Litterfall, Carbon and Nitrogen Storage

The data on litterfall, carbon, and nitrogen storage status of vegetation were analyzed using GraphPad Prism (version 9.1.0). The correlations were obtained for each of the spectral vegetation indices (NDVI, SAVI, and NDMI) with litterfall, C, and N storage for different vegetation types of AABR. The data of ground sample plots were overlaid on vegetation indices images to extract the representative data under Arc-GIS (version 10.3) platform. The spectral vegetation indices (viz. NDVI, SAVI,

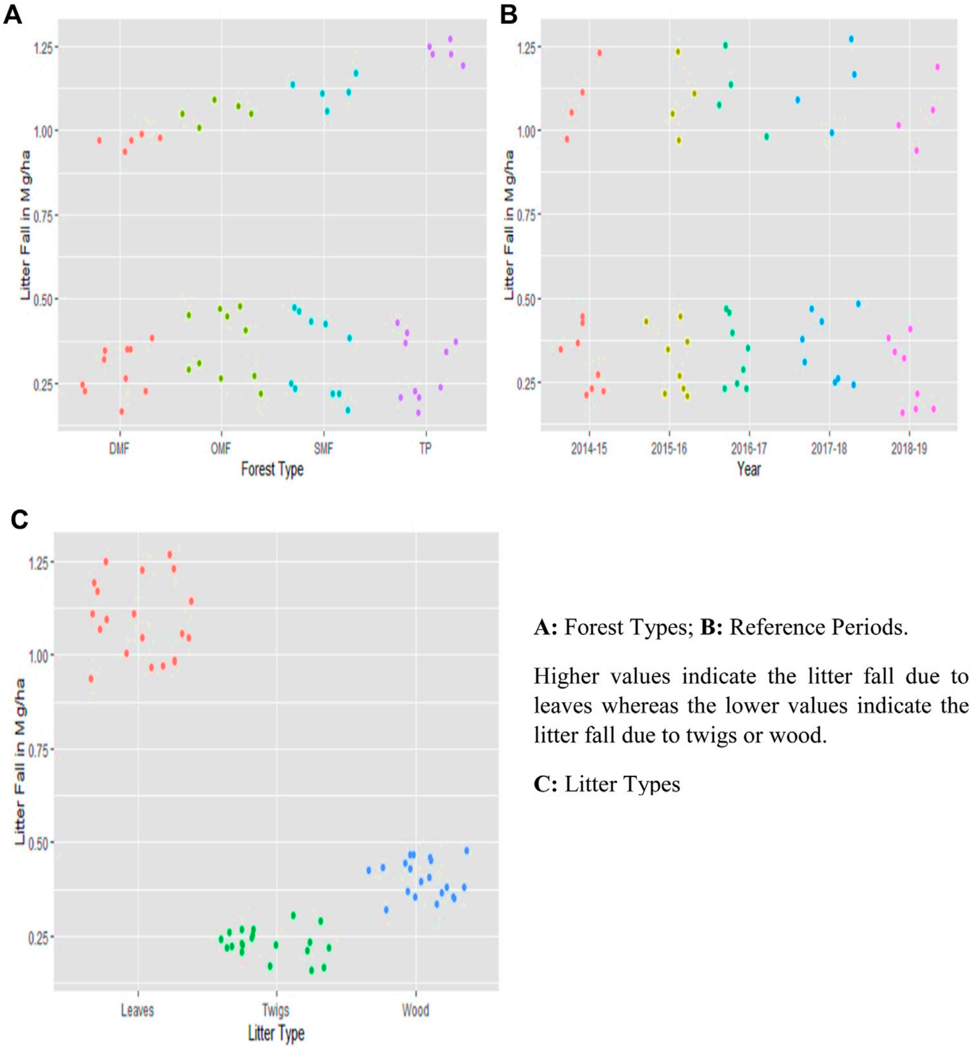

FIGURE 4 | Litter fall observation for understanding sustainable bioeconomic patterns in parameters. **(A)**: forest types; **(B)**: reference periods. Higher values indicate the litter fall because of leaves, whereas the lower values indicate the litter fall because of twigs or wood. **(C)**: litter types.

and NDMI) derived from satellite data were correlated along with ground-measured structural and functional variables and tested at $p \leq 0.01$.

RESULTS

Sustainable Litterfall Analysis

Litterfall estimation for observing the sustainability was carried out for four different vegetation types for a period of five years, from 2015–2019. The mean *LF* (Mg/ha) for DMF, OMF, SMF, and TP was found to be 0.52 ± 0.34, 0.59 ± 0.35, 0.59 ± 0.40, and 0.61 ± 0.46 (**Supplementary Table S1** and **Figure 3B**). The mean *LF* (Mg/ha) for selected for the reference periods 2015, 2016, 2017, 2018, and 2019 was found to be 0.57 ± 0.39, 0.57 ± 0.39, 0.59 ± 0.39, 0.61 ± 0.40, and 0.53 ± 0.40 (**Supplementary Table S1**). The monthly estimation of litterfall for all the vegetation types from 2015 to 2019 is shown in **Figure 2III**. The mean annual litterfall is 4.19 ± 0.305 Mg/ha. Maximum litterfall was observed in November and minimum in June. The temperature was at its peak in May and low in December and January (**Figure 3A**). With regards to precipitation, maximum was recorded in July and minimum in November (**Figure 3B**). In the case of different litter types, the mean *LF* because of leaves, twigs, and wood was found to be 1.09 ± 0.10, 0.23 ± 0.04, and 0.40 ± 0.05 (**Supplementary Table S1** and **Figure 3A**). A comparatively higher value of standard deviations for *LF* in four selected forest types and five selected reference periods when compared to the three litter types is observed (**Supplementary Table S1**). This is because of the huge difference between the *LF* because of leaves and that because of twigs or wood for each forest type and each reference period (**Figures 4A–C**).

TABLE 3 | Significant Differences Obtained in Post-Hoc Tests for sustainable management.

Factor	Categories	Difference in y (*p*-value)	Difference in terms of LF (Mg/ha)
Forest Type	OMF-DMF	0.03 (<0.01)	0.03
	SMF-DMF	0.02 (<0.01)	0.02
	TP-DMF	0.02 (0.02)	0.02
Litter Type	Leaves—Twigs	0.33 (<0.01)	0.29
	Leaves—Wood	0.23 (<0.01)	0.21
	Wood—Twigs	0.10 (<0.01)	0.08
Assessment Period	2015–2019	0.02 (0.03)	0.02
	2016–2019	0.02 (0.03)	0.02
	2017–2019	0.03 (<0.01)	0.03
	2018–2019	0.04 (<0.01)	0.04

The findings for 3-way ANOVA are presented in **Supplementary Table S2**, and the following post-hoc tests are presented in **Table 3**. The within-group variations for all the three factors considered for ANOVA are found to be significant (p-value for F < 0.01) (**Supplementary Table S2**). This indicates that the mean for different forest types (litter types/reference periods) are not all the same. At least one of the categories from DMF, OMF, SMF, and TP differs from the rest in this aspect.

Similar interpretations hold for categories of litter types and reference periods. The post-hoc tests indicate that DMF has a significantly different mean when compared to the rest of the three forest types (**Table 3**). When the other factors are held constant, the mean for DMF is 0.03 Mg/ha lesser than that of OMF. The mean for DMF is lesser than that for SMF and TP by 0.02 Mg/ha when the other factors are held constant. Keeping other factors constant, the mean for leaves is found to be more than that for twigs and wood by 0.29 Mg/ha and 0.21 Mg/ha. Under similar conditions, the mean of wood is found to be more than that of twigs by 0.08 Mg/ha (**Table 3**). The mean *LF* for the reference period 2019 was found to be significantly different from other reference periods, namely, 2015, 2016, 2017, and 2018. It was found to be lower than that of the reference periods, i.e., 2015, 2016, 2017, and 2018 by 0.02 Mg/ha, 0.02 Mg/ha, 0.03 Mg/ha and 0.04 Mg/ha**.** The seasonal-wise determined litterfall biomass values were observed in the winter season, whereas the values in the remaining two seasons were almost alike (**Figures 3**, **5**). The season litterfall pattern observed in TP, SMF, and DMF followed the pattern of winter > summer > rainy (**Figure 3A**). The order differed in OMF, where the pattern observed was winter > rainy > summer. A variation was observed in component-wise (leaves, wood, and twigs) analysis of mean seasonal litterfall. Leaves followed the order of winter > rainy > summer, whereas wood and twigs followed the pattern of winter > summer > rainy (**Figure 3B**).

Fine Root Biomass and Decomposition Rate of Sustainable Litterfall (Turnover of Litter)

The fine root biomass was analyzed for three parameters, namely, seasonality, depth of soil (0–30 cm and 30–60 cm), and different vegetation types (**Table 4**). The mean fine root biomass (g/m^2) was observed to be higher in the rainy season (1.35 g/m^2) followed by winter (1.06 g/m^2) and summer (0.89 g/m^2) seasons. In the case of depth zones, the mean fine root biomass value was observed higher in 0–30 cm (0.95 g/m^2) and lower in 30–60 cm (0.29 g/m^2). The turnover rate in different forest types varied from 0.50–0.62, indicating approximately 45–62% turnover of litter in a year. The turnover time of litter in different forest types varied from 1.61–1.98 y. The minimum time was estimated in TP, and the maximum was recorded in OMF, followed by SMF and DMF.

Correlation Between Vegetation Indices (SAVI, NDVI, and NDMI), Litterfall, Carbon and Nitrogen Storage

The mean annual litterfall of TDFs is 4.19 ± 0.305 Mg/ha/y (**Figure 6A**). The total C sequestration in various components of litter (i.e., leaves, wood, and twigs) was 4.64 Mg/ha with a mean of 4.4 ± 1.16 Mg/ha (**Figure 6B**). Leaves contributed the highest to the total litterfall production, followed by wood and twigs with a mean of 0.73 ± 0.42 Mg/ha, 0.25 ± 0.02 Mg/ha, and 0.17 ± 0.03 Mg/ha. The total N storage in all the components of litter was 0.062 Mg/ha with a mean of 0.02 ± 0.002 Mg/ha (**Figure 6C**). Similar to the C content, the storage of N content was higher in leaves, followed by wood and twigs. Pearson correlation was used to analyze the important spectral vegetation indices (NDVI, SAVI, and NDMI), litterfall, and C & N storage in the dry tropical forest of AABR as summarized in **Table 5**. The SAVI, NDVI, and NDMI images are represented (**Figures 7A–C**). Results indicated that the SAVI and NDVI values were positively correlated with litterfall, C, and N storage. The study found a positive correlation between the litterfall and nutrient storage (C and N) with soil-adjusted vegetation index and other vegetation indices. Pearson Correlation among SAVI with pooled data of litterfall and nutrient storage (C and N) were performed and shown in **Table 5**. Litterfall and C storage values were estimated following stratified random sampling, and noticed that there was a significant correlation between the NDVI and SAVI. It was evident from the results that the litterfall and C storage were positive and highly significant (both at 5 and 1 percent level) and strongly correlated with NDVI and SAVI, whereas they were not significant with NDMI. Among the forest types, DMF recorded the highest values of NDVI, SAVI, and NDMI.

Temperature and Precipitation as Predictors of Litterfall

Three different models (*M1*, *M2*, and *M3*) were developed to establish the relationship between litterfall, temperature, and precipitation (**Table 6** and **Figure 8**). Model *M1* and *M2* were utilized as predictor models of ln (LF) with P and T as predictors. Model *M3* incorporates both P and T as predictors of ln (LF). Homoscedasticity for the selected was tested using the Breusch-Pagan test (Breusch and Pagan, 1979), p-values for *M1*, *M2*, and

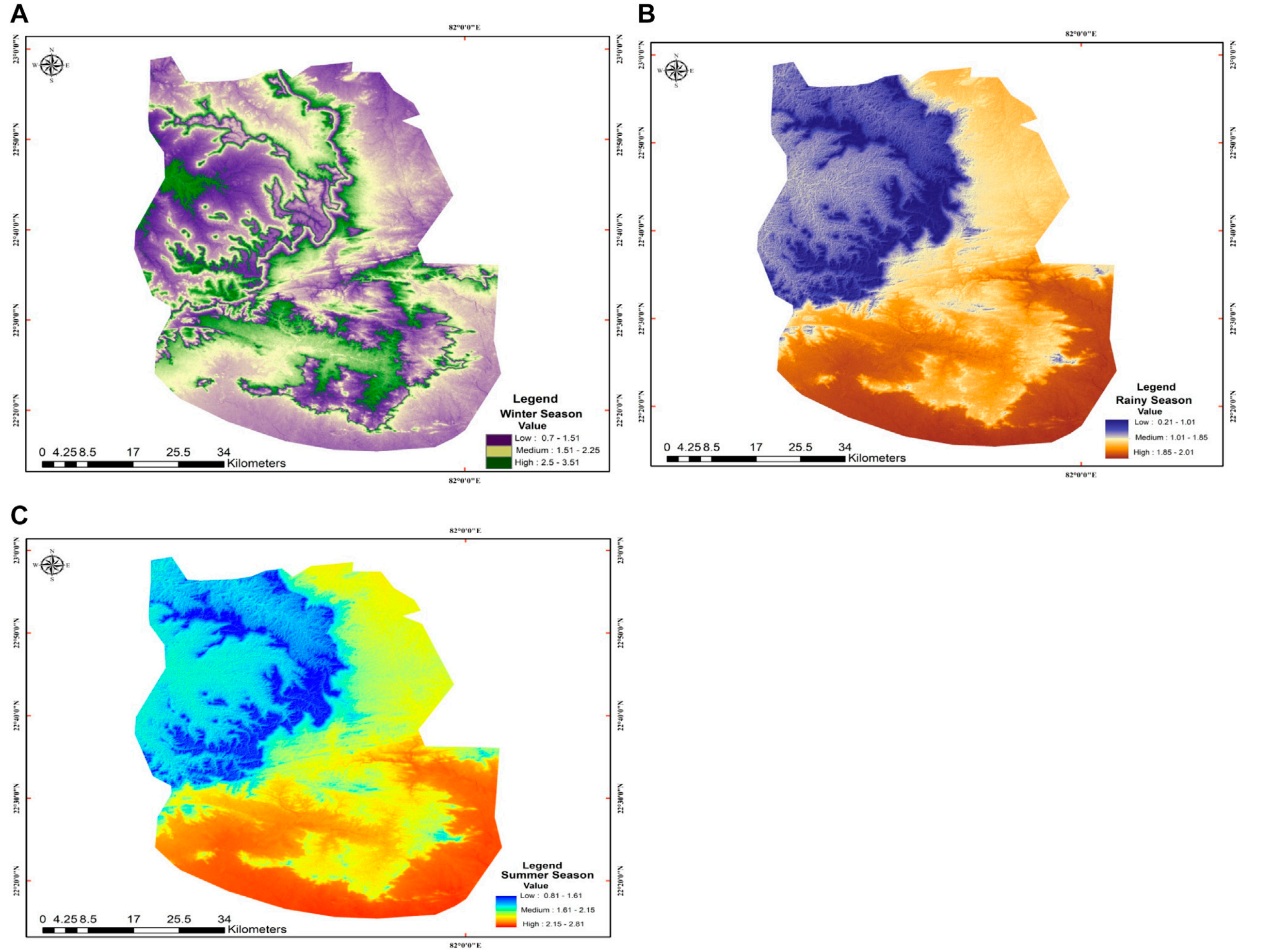

FIGURE 5 | Seasonal litterfall (Mg/ha) of different vegetation types in AABR showing sustainable litterfall pattern. **(A)**: winter season. **(B)**: rainy season. **(C)**: summer season.

TABLE 4 | Fine Root Biomass (Mg/ha), Turnover rate (K), and Turnover time (t) of litter in Forest type during 2015–2019.

Forest type	Rainy		Winter		Summer		Turnover rate (K)	Turnover time (t)
	(0–30 cm)	(30–60 cm)	(0–30 cm)	(30–60 cm)	(0–30 cm)	(30–60 cm)		
TP	0.85	0.34	0.64	0.35	0.59	0.29	0.62	1.61
SMF	1.02	0.44	0.78	0.37	0.64	0.3	0.59	1.65
DMF	1.18	0.51	0.84	0.38	0.67	0.31	0.58	1.62
OMF	0.74	0.32	0.58	0.32	0.51	0.26	0.50	1.98

M3 are 0.38, 0.87, and 0.19, respectively. The normality of the model residuals examined using the Anderson–Darling test, *p*-values for *M1*, *M2,* and *M3* are 0.95, 0.24, and 0.39, respectively.

The model *M1* (**Tables 2**, **6** and **Figure 9A**) indicated that *LF* is a decreasing function of *P*. The predicted value of *LF* at minimum precipitation (0 mm) is 0.40 Mg/ha. The geometric mean of *LF* for observations with 0 cm precipitation is found to be 0.53 Mg/ha. The maximum value attained by *P* in the data set is 465.24 mm. The *LF* observed at this value of *P* is 0.22 Mg/ha and as per *M1* the predicted *LF* at this value of *P* is 0.21 Mg/ha. Similar to model *M1*, model *M2* (**Table 2** and **Figure 9B**) indicates that *LF* is a decreasing function of *T* (**Tables 2** and **6** and **Figure 8B**). The maximum and minimum values of *LF*, as predicted by *M2* are 0.51 Mg/ha (at $T = 15.07$°C) and 0.21 Mg/ha (at $T = 35.23$°C). These observed values are 0.39 Mg/ha (at $T = 15.07$°C) and 0.38 Mg/ha (at $T = 35.23$°C). Model *M3* (**Tables 2**, **6**)

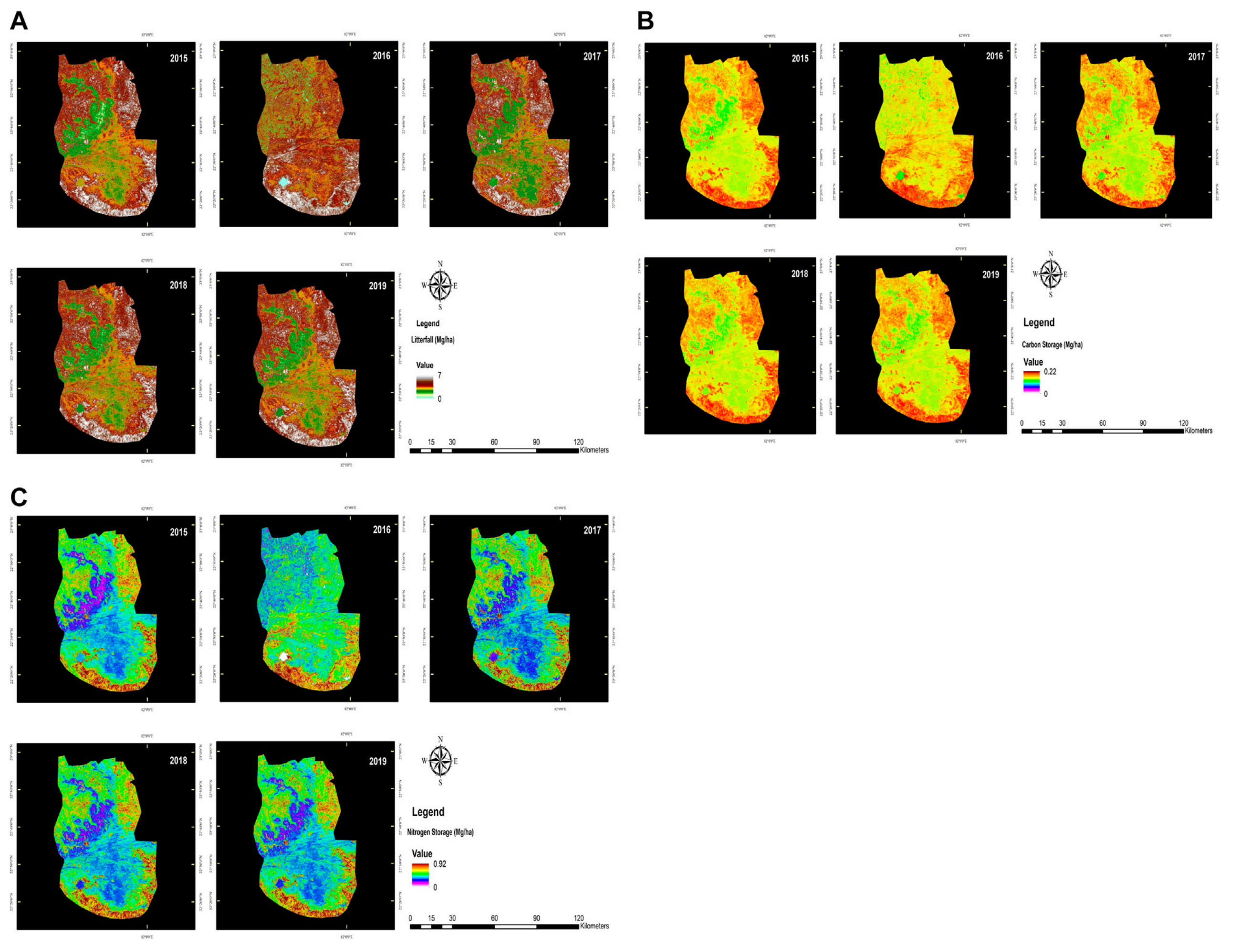

FIGURE 6 | Understanding sustainability-estimation of annual litterfall (Mg/ha), carbon and nitrogen storage (Mg/ha) under different vegetation types in AABR. **(A)**: annual litterfall (Mg/ha); **(B)**: carbon storage (Mg/ha); **(C)**: nitrogen storage (Mg/ha).

indicates a complex interaction between *P* and *T*. *M3* predicts a maximum value for *LF* (0.75 Mg/ha) at 0 mm precipitation and 15.07°C of temperature. As per *M3*, the minimum *LF* (0.22 Mg/ha) was obtained at 465.54 mm precipitation and 15.07°C of temperature. In what follows, the predictions for sub-datasets S_1, S_2, S_3, and S_4 are described.

The set S_1 consists of 20 sample points covering the months of November, December, January, and February. The temperature for S_1 varied in the range of 15.7–23.36°C with a median of 19.29°C (**Table 6**). The precipitation for the sub-dataset varied in the range of 0–20.46 mm with a mean value of 6.13 mm. The average *LF* for S_1 is found to be 0.40 Mg/ha. The *LF* for S_1, as predicted by the models *M1*, *M2*, and *M3* were 0.39 Mg/ha, 0.43 Mg/ha, and 0.40 Mg/ha. The set S_2 consists of 8 sampled points spread mostly over January, March, September, October, and December. The temperature of S_2 varied from 15.36 to 24.73°C with a median of 23.76°C. The precipitation for S_2 varied in the range from 27.46 to 237.51 mm, with a mean value of 77.01 mm. The average *LF* for S_2 was found to be 0.31 Mg/ha. The *LF* for S_2, as predicted by the three models, was 0.31 Mg/ha, 0.35 Mg/ha, and 0.29 Mg/ha. The set S_3 consists of 23 sample points spread over March, April, May, June, July, August, and September. The temperature for S_3 was observed to be in the range of 25.03–35.23°C with a median of 26.26°C (**Table 6**). The precipitation for S_3 varied in the range of 26.02–465.54 mm with a mean value of 221.26 mm. The average *LF* for S_3 was found to be 0.26 Mg/ha. The predicted values of *LF* for S_3, as predicted by the three models, were 0.25 Mg/ha, 0.31 Mg/ha and 0.26 Mg/ha. The set S_4 consists of 9 sample points spread over March, April, and May. The temperature for S_4 was observed to be in the range of 26.14–34.40°C with the median at 32.50°C. The precipitation for S_4 varied in the range of 0.04–24.11 mm with a mean of 8.36 mm. The average *LF* for S_4 was found to be 0.36 Mg/ha. The predicted values of *LF* for S_4, as predicted by the three models, were 0.38 Mg/ha, 0.24 Mg/ha, and 0.29 Mg/ha.

TABLE 5 | Pearson correlations among important spectral vegetation indices (NDVI, SAVI, and NDMI), litterfall, carbon and nitrogen storage in dry tropical forests of AABR.

Parameter	NDVI	SAVI	NDMI	C storage	N storage	Litterfall
NDVI	1					
SAVI	0.71**					
NDMI	0.55*	0.41*	1			
C storage	0.62**	0.53*	0.23 **NS**	1		
N storage	0.65**	0.52*	0.31 **NS**	0.74**	1	
Litterfall	0.68**	0.65*	0.43*	0.61**	0.67**	1

***Correlation is significant at the 0.01 level (2-tailed).*
**Correlation is significant at the 0.05 level (2-tailed).*
***NS**, Non-significant.*

DISCUSSION

A seasonal litterfall epitomizes a crucial process in C and elemental cycling of the forest ecosystems (Wang et al., 2016). The major aim of the present study was to estimate the annual and seasonal litterfall pattern for 5 years from four different vegetation types of the tropical dry forest. The results revealed a positive relationship between the vegetation indices with the present litterfall along with the nutrient storage. The regression models were developed to establish the association between the litterfall and the climatic measures such as temperature and precipitation.

The short-term and long-term studies on estimating the annual litterfall patterns showed close relation in maintaining the C balance and sustainability within the forest ecosystems. The litter not only significantly contributed to the global C cycle but played a vital role in the supply of OM and enriching nutrients in the soil, which control intrinsic self-sustainable functions of the forest ecosystem (Sayer et al., 2011). The majority of the studies focused on analyzing the forest patterns for >5 y in different forest zones, i.e., tropical forests (Aryal et al., 2015), tropical dry forests (Souza et al., 2019), tropical rainforests, sub-tropical forests (Yang et al., 2004), temperate forests (Thakur et al., 2021). Few studies considered assessing the litterfall throughout for 5 y (Williams-Linera et al., 2021), 10 y (Wang et al., 2016), and >10 y (Leishangthem and Singh, 2021). Few studies narrowed down the range of field sites and analyzed litterfall from the specific tree species micro-sites. Few of the meta-analysis studies emphasize the long-term data as it is required for an improved understanding of the litter dynamics and the biogeochemical cycles involved within the forest ecosystems (Liu et al., 2021). Sustainable resource use efficiency of soil system depends upon the activeness of the microfaunal population and depends upon the C:N ratio. The addition of OM with the desirable C:N ratio improves the nutrient status of soil and enhances the soil quality (Kumar et al., 2021b). The debris and leaf fall from the trees on the forest floor make the soil porous, spongy, and biologically active. It provides a habitat for millions of micro-flora and macro-fauna essential for the decomposition of litter and nutrient cycling (Panwar and Gupta, 2015). The root systems of the trees bind the soil, particularly in the ecologically fragile and risk-prone areas that create barriers to soil erosion.

The total annual litterfall pattern of the world's tropical forests is presented in **Supplementary Table S3**. In the present study, the mean annual litterfall coincides with the global estimation provided (Souza et al., 2019). In addition, the litterfall from the TDFs of India is consistent with the global litterfall patterns of the tropical forest, as mentioned in **Supplementary Table S3**. Results from Zhang et al. (2014) revealed that global litterfall patterns for tropical forests and tropical rainforests are equivalent. In the present study, leaves contributed ~64% of the total annual litterfall, which is similar to the findings of previous studies (Araújo et al., 2019). The litterfall significantly correlates with the vegetative phenology of the plants since it is observed that the majority of the litterfall consists of leaf litter (Araújo et al., 2019). In TDFs, the ratio of leaf fall to the living leaf biomass decreases drastically with the increase in soil moisture, which in turn reflects the sensitivity of leaf turnover to changes in water availability (Van Bloem et al., 2003). Within the variation in annual litterfall production, seasonal variations were also observed throughout the year. From the present study, maximum litterfall production was detected in the winter season, i.e., ~ 40%, while the remaining seasons contributed 30% each. Monthly studies (**Figure 2**) reveal that the cold–dry season (November–December) was favorable for litterfall production, followed by the hot–dry season (April–May). Similar observations were reported in the tropical rainforests, where the cold-dry seasons were ideal for the maximum litterfall input (Darro and Swamy, 2020). The present result contradicts the previous studies carried out in tropical forest ecosystems of India (Thakur et al., 2014). The litterfall production was maximum in summer, followed by the winter and monsoon seasons. As the data was collected for only one year, this could be the possible reason for such variation, which ultimately supports the studies carried out by Jia et al. (2020) and Wang et al. (2016), emphasizing the importance of long-term data analysis for precise litterfall estimation.

Remote sensing and GIS-associated techniques have been playing a key role in the detection and estimation of functional processes and biomass storage in tropical forests (Thakur et al., 2019), sub-tropical forests (Wang et al., 2016), temperate deciduous forests (Thakur et al., 2021), tropical montane forest (Wang et al., 2016), boreal forests (Zheng et al., 2004), deciduous forests (Birky, 2001)

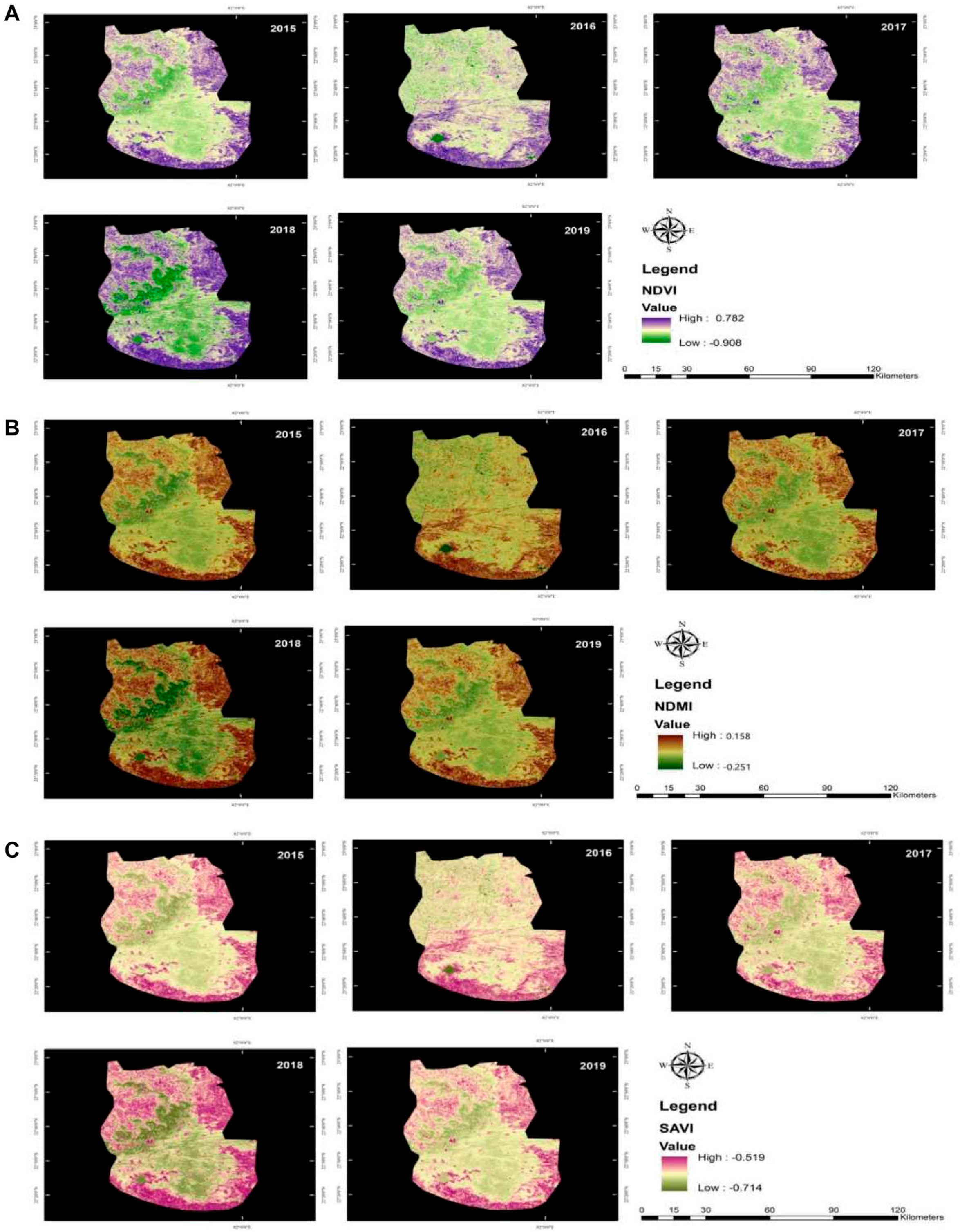

FIGURE 7 | Spectral vegetation indices (NDVI, NDMI, and SAVI) of AABR

TABLE 6 | Model based predicted *LF* for different sub-datasets

Group	Median T (°C)	Mean P (mm)	Mean LF (Mg/ha)	Model Predicted LF for median T and mean P (Mg/ha)		
				M1	M2	M3
S_1	19.29	6.13	0.40	0.39	0.43	0.40
S_2	23.76	77.01	0.31	0.31	0.35	0.29
S_3	26.26	221.26	0.26	0.25	0.31	0.26
S_4	32.50	8.36	0.36	0.38	0.24	0.29

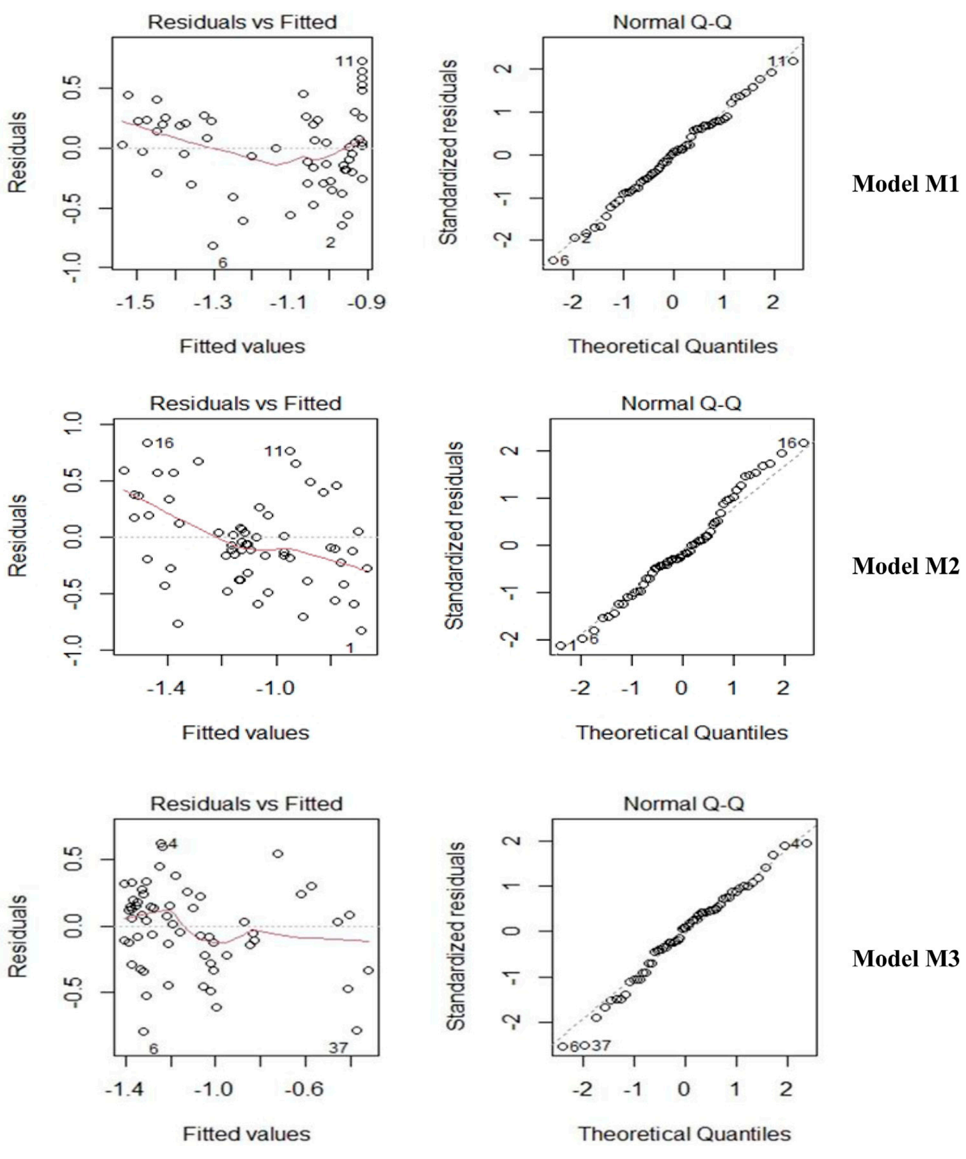

FIGURE 8 | Residual plot and normal QQ plot.

and Pine forests (Ozdemir and Yilmaz, 2020). Shen et al. (2019) demonstrated the conjunctive use of remote sensing and GIS-based techniques coupled with statistical analysis in estimating global litterfall patterns. It has been considered the largest dataset of litterfall patterns using geo-statistics. The present study revealed a positive and significant correlation between SAVI and NDVI (**Figure 6** and **Table 5**) with litterfall and carbon storage for different

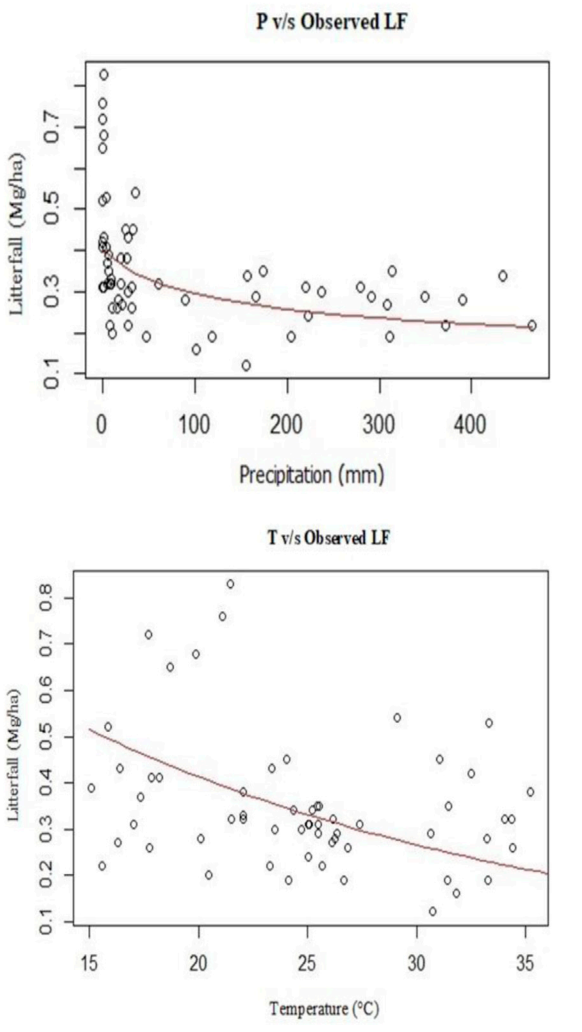

FIGURE 9 | Scatter plot of the selected parameters v/s litterfall. **(A)**: Mean precipitation (mm) v/s litterfall. Observed LF was predicted by model M1. The curve gives the predicted litter fall over the range of precipitations as per the model M1. **(B)**: mean temperature (°C) v/s litterfall. observed LF was predicted by model M2. The curve gives the predicted litter fall over the range of temperature as per the model M2.

vegetation types in the study area, which matches with reports of previous studies (Thakur et al., 2019). Spectral models were developed for the estimation of biomass and NPP using vegetation indices [NDVI, SAVI, and transformed vegetation index, and advanced vegetation index] (Thakur et al., 2019), considering forest growth rate as a function of climatic parameters such as temperature, moisture and light intensity (Birky, 2001).

Numerous studies evidenced a strong correlation between the vegetation indices such as NDVI, NDMI, and SAVI with ecological variables in various forest ecosystems (Thakur et al., 2019). The results of the studies revealed that NDVI is a key variable that strongly correlated to biomass C of vegetation, whereas N values were not found significant in any of the tested spectral vegetation indices (NDVI, SAVI, and NDMI) (**Figure 6** and **Table 5**). Studies reveal that NDVI is positively correlated with litter biomass (Thakur et al., 2019), and the temporal anomalies in NDVI could be a good indicator of stress conditions in an ecosystem (Wang et al., 2020). Ozdemir & Yilmaz (2020) estimated litterfall biomass in pine forests of Turkey using NDVI extracted from Rapid-Eye, Spot-5, and Aster Satellite imageries along with the environmental factors such as heat and radiation index. In one of the interesting studies, i.e., Yang et al. (2018) developed a geometrical-optical based model using MODIS data along with statistical analysis to estimate the forest litter moisture of sub-tropical forests. This method separates the background reflectance from the optical remote sensing imagery, and it has proved to be an efficient model as it can also provide information about the undergrowth vegetation. Few studies that were carried out in tropical and sub-tropical forests (Wang et al., 2016) attempted to use the remote sensing time series such as MODIS data along with the vegetation indices, i.e., NDVI and climatic variables such as temperature and precipitation data, to estimate the litterfall production. Such studies demonstrated the importance of exploiting MODIS temporal data in monitoring the biogeochemical cycles in forest ecosystems.

Climatic variables such as temperature and precipitation are essential as they influence the annual litterfall production in forest ecosystems. A negative correlation was observed in the present study between the mean annual precipitation (mm) and mean litterfall (Mg/ha/y) which corroborates with the previous studies (Morffi-Mestre et al., 2020). Few studies in dry forests exhibited a close association between precipitation and litterfall (Darro and Swamy, 2020). The monthly dataset (**Figure 2**) highlights a low mean temperature (16–19°C) with low mean precipitation (0.1–7.5 mm), leading to the monthly high mean litterfall production (0.4–0.7 Mg/ha). This implies the importance of a monthly estimation of climatic parameters and litterfall in long-term studies. Zhang et al. (2014) concluded that precipitation is a major constraining factor in regulating litterfall in tropical forest ecosystems. Plants adopt a mechanism in which leaves shed is because of intense water stress, and this is most visible in the dry season (Zhang et al., 2014). Because the primary productivity is mostly controlled by the quantity and duration of precipitation, the seasonal fluctuations in precipitation limit and control the productivity and nutrient dynamics of seasonally dry forest ecosystems (Araújo et al., 2019). The duration and the quantity of the litterfall are heavily controlled by various abiotic parameters such as water, temperature, and precipitation and also depend on nutrient availability in the soil (Souza et al., 2019). Similar to tropical forests, the key drivers, such as temperature and precipitation, are also responsible for the change in litterfall production. The results of the study showed that there were negative effects of LT on total litterfall production (Wang et al., 2020). Because of the higher root: shoot biomass, dry tropical forests have the advantage of maintaining the metabolism at lower soil and leaf water potentials in comparison to temperate or humid tropical forests (Van Bloem et al., 2003).

Microfaunal populations also exert a vital influence on the sustainable and judicious decomposition of litter and regulation of litter dynamics. The soil micro-and macro-fauna influence the decomposition process as the litter accumulated on the surface layer serves as a source of organic food materials for soil fauna and ensures the efficient cycling of nutrients within a forest community (Preusser et al., 2021). Litter degradation and its conversion into humus accompanied by the decomposition of litter by microbial activities enhance the mineralization process and release nutrients in available forms from complex organic compounds (Cotrufo et al., 2010). Climatic factors, litter quality, and activity microorganisms regulate the standing state and litter turnover. It is widely demonstrated that the rate of annual litter decomposition (k-value) increases with temperature, precipitation, and litter quality in certain limits across the forest ecosystems, while it decreases with elevation characterized by LT, precipitation regimes in poor quality litter containing high lignin (Zhang et al., 2008). The temperature and drought are detrimental climatic effects that increase the k-value of various litter types in heterogonous forest landscapes (Jasińska et al., 2020). The litterfall and litterfall dynamics are key functionaries in the TDFs ecosystem, mainly hang on stand types and climatic variables, and are considered to be a storehouse of carbon for maintaining sustainable global climate change (Santos et al., 2012).

CONCLUSION

The present study is developed based on field and satellite data to understand the effect of stand type, seasons, and climatic variables on the litterfall in the seasonally dry tropical forests in Central India. The study indicates that litterfall in TDFs is significantly influenced by vegetation functional type, seasons, and climatic variables such as temperature and precipitation. The study linked to understanding sustainability in relation to litterfall leading to biomass and carbon sequestration for global climate change. The results revealed that the maximum litterfall biomass was obtained in the cold-dry season and that leaves contributed to most of the total litterfall production in the dry tropical forest. A positive correlation was observed between the litterfall and nutrient storage with soil-adjusted vegetation index and other vegetation indices. It will be possible to fairly predict the sustainable decomposition of litterfall using vegetation indices derived from remote sensing. These, in turn, will help in understanding both vegetation and soil carbon dynamics in the forest ecosystems. The study also demonstrated that both temperature and precipitation affected the litterfall in different functional types of vegetation. The results depicted that the precipitation is inversely proportional to the annual litterfall production in a dry tropical forest. Thus, the present study concludes that the vegetation types of AABR have significant potential to improve litter production and further store a large quantity of C and N from the atmosphere in the future to mitigate global climate change sustainably.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/**Supplementary Material**, further inquiries can be directed to the corresponding author.

AUTHOR CONTRIBUTIONS

TT: conceptualization, methodology, writing-original draft, writing—review and editing, supervision. KE: software, formal analysis, writing—original draft, writing—review and editing. AT: data collection, analysis, review. AK: writing—review and editing. SB: software, formal analysis, writing-review, and editing. SS: formal analysis, writing—review and editing. AB: writing—review and editing. MK: writing-review and editing.

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SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fenvs.2022.940614/full#supplementary-material

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NOMENCLATURE

Abbreviation

C Carbon

C.G. Chhattisgarh

LF Litterfall

GIS Geographic Information System

IVI Important value index

SAVI Soil-Adjusted Vegetation Index

NS Non-Significant

R Red

R^2 Coefficient of determination

VI Vegetation Index