

Article

Three Decades of Remote Sensing Reveal Contrasting Trends of Biomass and Tree Regeneration in Argentine Dry Forests

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Abstract

Dry forests are increasingly threatened by degradation, which determines their structural integrity, functional capacity, and the ability to provide essential ecosystem services. Degradation is the consequence of processes that reduce the different attributes of forests. This study aimed to (i) identify remote sensing proxies for above-ground biomass (AGB) and tree regeneration in three ecoregions of dry forest localized in west Argentina; (ii) analyze the temporal dynamics between 1993 and 2023; (iii) assess the role of precipitation in their temporal variability, and (iv) map their spatial distribution. The median Tasseled Cap Transformation Wetness (TCTW) was the best-performing spectral proxy for AGB, while median Enhanced Vegetation Index (EVI) best captured tree regeneration. In the time series of TCTW, no significant breakpoint was detected; however, a pronounced decline in the median EVI occurred in 1998 in the Monte of Plains and Plateaus and Monte of Hills and Basins ecoregions, particularly near watercourses. In the Dry Chaco, tree regeneration recovered after 2013; however, a decline after a breakpoint coincided with decreased precipitation. Overall, AGB and tree regeneration exhibited contrasting temporal and spatial patterns, underscoring the heterogeneity of dry forests. A weakening relationship between precipitation, a key driver of forests, and forest attributes suggests the influence of other factors, including topography and land use change.

Keywords: above-ground biomass; forest dynamics; Landsat time series; precipitation variability; vegetation indices; Enhanced Vegetation Index; Tasseled Cap Transformation Wetness



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1. Introduction

Drylands cover nearly 41% of the Earth's terrestrial surface, support more than 2.5 billion people, and sustain over half of the global livestock population [1,2]. Under specific climatic, topographic, and edaphic conditions, dry forests develop as well-adapted vegetation communities that perform essential ecological and socioeconomic functions, while helping to mitigate harsh environmental conditions. Their structure and functioning are strongly dependent on precipitation, which in turn constrains their capacity to provide a wide range of provisions, regulations, support, and cultural services [3] to local

communities. Among the most relevant ecosystem services delivered by dry forests are soil stabilization, watershed protection, and the supply of fuelwood and fodder for livestock [4].

In the context of climate change and the expansion of anthropogenic activities, dry forests are increasingly threatened by degradation, leading to a loss of ecosystem services that sustain human well-being. At present, drylands are expanding due to climate change, and it is projected that they will cover half the world's land surface by the year 2100 under moderate emissions scenarios [5]. Forest degradation is now recognized globally as a critical environmental, social, and economic challenge, affecting both ecosystem functioning and the livelihoods that depend on it [6,7]. Consequently, assessing the magnitude of degradation and developing strategies to halt or reverse its impacts are essential to conservation planning, sustainable land management, and ecological restoration in dry forests.

Remote sensing has revealed global greening trends across drylands over the past three decades [8], particularly in regions such as the Tibetan Plateau and the western United States [9], while vegetation declines have been reported in both the Northern and Southern Hemispheres [10]. These contrasting patterns reflect the high sensitivity of dryland ecosystems to climate variability. Precipitation is the primary limiting factor controlling productivity, tree regeneration, and vegetation cover in dry ecosystems [11]. In arid and semi-arid regions, precipitation is typically infrequent, highly variable in space and time, and often occurs in short, intense events that strongly influence plant water availability and growth patterns. Other climatic variables (e.g., temperature, solar radiation) also shape ecological responses, but their effects are marginal compared to the dominant role of precipitation [12].

Forest degradation is broadly defined as a reduction in the capacity of forests to provide goods and services [13]. However, the concept has been interpreted in multiple ways depending on the disciplinary focus and study objectives [14]. In this study, the conceptual framework proposed by Vásquez-Grandón et al. [15] was adopted, which defines a degraded forest as the result of processes that negatively affect its attributes. This framework proposes three criteria to identify degradation: structure, composition, and regeneration capacity. Altered forests are characterized by moderate to low levels of tree species regeneration depending on the degree of degradation. Additionally, regeneration is linked to the presence of adult seed trees and the successful establishment of these seeds. Estimates of above-ground biomass (AGB) from allometric equations are an integrated variable structure [16]. It is necessary to use different structure metrics such as height, diameter, and canopy tree cover to apply these equations. Particularly, degraded forests are characterized by changes in diameter distribution and reductions in canopy cover due to adverse conditions and intensive anthropic activities.

Given the threatened status of many dry forests, these challenges have motivated extensive remote sensing research over the last decade [17,18]. Different analytical approaches have been developed to assess spatial and temporal variations in tree regeneration and AGB [19], including visual interpretations of high-resolution imagery [20] and the use of multi-seasonal datasets [21]. More advanced techniques such as spectral mixture analysis [22] and Time Series Segmentation (TSS-RESTREND) [23,24] have further enhanced the capacity to monitor forest conditions.

Several authors [25–27] have argued that identifying locations where degradation disrupts the relationship between vegetation and precipitation—hereafter referred to as breakpoints—can enhance the accuracy of dryland vegetation assessments. TSS-RESTREND operates by fitting a statistical relationship between climatic variables and vegetation dynamics. This methodology integrates RESTREND (RESidual TREND analysis) [28] with BFAST (Breaks For Additive Season and Trend) to improve the detection of breakpoints. The BFAST [29] algorithm works by breaking time series data down into

seasonal, trend, and remainder components, coupled with the detection of abrupt changes in both the trends and seasonal components [27]. However, this is dependent on an annual phenological signal in vegetation. Evidence from arid regions of Australia demonstrates that TSS-RESTREND (BFAST + RESTREND) improves the detection of forest degradation, unlike BFAST alone [24].

In this study, spectral variables derived from passive sensors are used with field-based measurements and predictive modeling to estimate key forest attributes. Following this, TSS-RESTREND was applied using the best-performing spectral proxy and precipitation as the climatic predictor to detect potential degradation processes in the dry forests of western Argentina. The specific objectives were to: (i) identify remote sensing proxies (from Landsat 5 and Landsat 8 data) for assessing above-ground biomass and tree regeneration in three dry forest ecoregions localized in west Argentina; (ii) analyze the temporal dynamics of dry forest attributes during the period 1993–2023, identifying trends and change points (breakpoints); (iii) assess the role of precipitation in the temporal variability; and (iv) map the spatial distribution of dry forest attributes across the three studied ecoregions. Long-term studies integrating consistent time series of remote sensing and precipitation data to assess key forest attributes such as above-ground biomass and tree regeneration remain scarce for the Dry Chaco and Monte desert. By addressing this gap, our study contributes valuable insights into dry forest dynamics in western Argentina and provides a scientific basis for improved management and conservation planning.

2. Materials and Methods

2.1. Study Area

The study was conducted in the eastern sector of San Juan Province, Argentina (Figure 1), within a dry forest ecosystem located in a transitional zone primarily characterized by the Monte desert physiognomy, with a smaller portion corresponding to the Dry Chaco. The area encompasses three ecoregions: Monte of Hills and Basins (MHB; Monte de Sierras y Bolsones), Monte of Plains and Plateaus (MPP; Monte de Llanuras y Mesetas), and Dry Chaco (DC; Chaco Seco). Climatic conditions vary markedly along the east–west gradient, with mean annual precipitation ranging from 50 to 350 mm [30], with a marked summer seasonality (December to March in this Hemisphere) and dry winters [31] and a mean annual temperature of 16 °C.

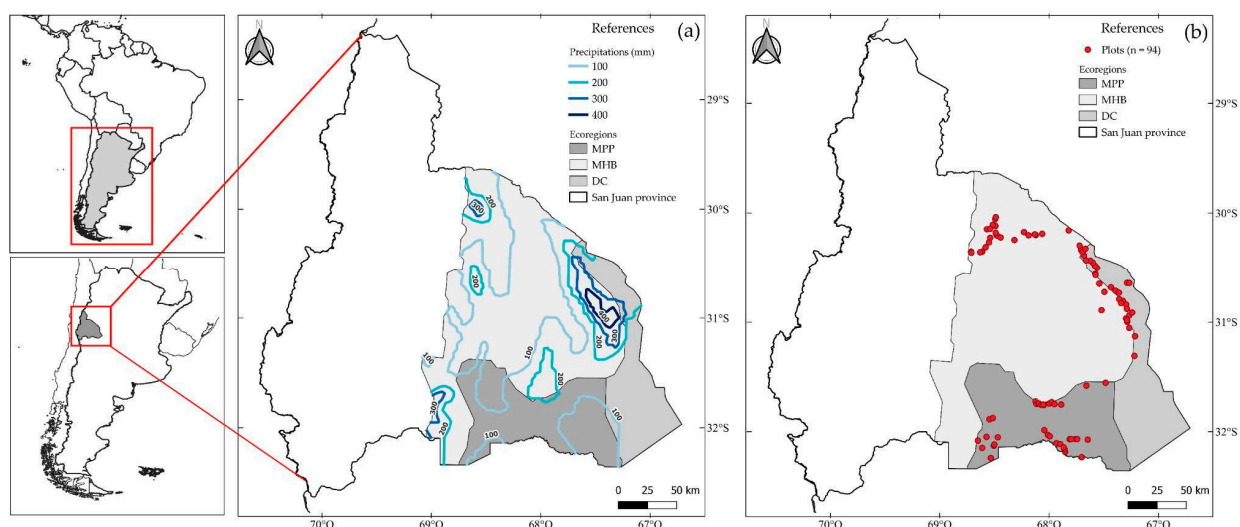


Figure 1. Map of the study area showing the spatial distribution of annual precipitation (a) and the distribution of sampled forest plots in the different ecoregions (gray) (b). MHB: Monte of Hills and Basins; MPP: Monte of Plains and Plateaus; DC: Dry Chaco.

Vegetation is dominated by xerophilous species, whose distribution is strongly conditioned by edaphic conditions and hydrological heterogeneity, typically forming patches in areas where water (from rainfall or groundwater) and nutrients are available. The dominant tree species are *Neltuma chilensis* and *N. flexuosa* (algarrobos), while *Geoffroea decorticans* (chañar) is more frequent in low-lying clay–silty soils. Smaller forest patches include endemic species such as *Bulnesia retamo* (retamo) and *Ramorinoa girolae* (chica), characteristic of piedmont dry forests. Less frequent species include *Vachellia caven* and *V. aroma* (espinillo). In relatively more humid areas, *Aspidosperma quebracho-blanco* occurs in association with *Neltuma* spp., accompanied by *Celtis pallida*, *Parkinsonia praecox*, *Jodinia rhombifolia*, and *Ziziphus mistol* [32].

Due to the prevailing arid conditions, large-scale disturbances such as extensive agricultural expansion are limited within the study area. Land use is primarily characterized by low-intensity, subsistence livestock grazing, which represents the dominant productive activity in the region [33]. Large commercial agricultural fields are generally located outside the dry forest matrix and are not embedded within the native woodland, resulting in relatively low levels of direct large-scale land conversion inside the study sites.

2.2. Data Analysis

The overall workflow of the data processing and analysis is presented in Figure 2, and the main steps are described in the following subsections.

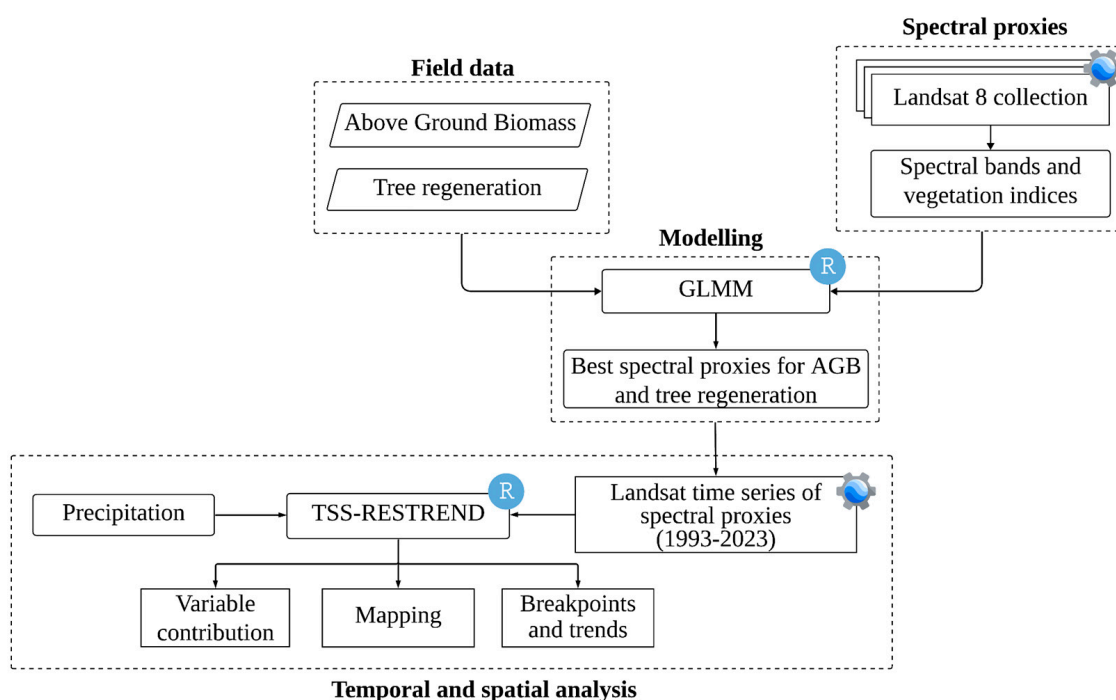


Figure 2. Workflow of methodological approach used to analyze dry forest attributes. Field data on above-ground biomass (AGB) and tree regeneration were integrated with Landsat time series imagery to derive spectral bands and vegetation indices. Generalized Linear Mixed Models (GLMM) were used to identify the best spectral proxies for AGB and tree regeneration. The selected proxies were analyzed as a time series (1993–2023) and combined with precipitation data using the Time Series Segmentation—RESidual TREND (TSS-RESTREND) approach to assess temporal dynamics and variable contributions. Finally, spatial mapping was performed to derive indicators of dry forest dynamics and degradation across the study ecoregions.

2.2.1. Field Data

Field surveys were carried out between June 2022 and October 2023, encompassing 94 plots of 1000 m² each, distributed across the three ecoregions of San Juan Province

(Figure 1). Sampling followed the methodological guidelines of the Second National Native Forest Inventory of Argentina [34], ensuring comparability with national inventories and previous studies in the region. A total of 37 plots were established in MPP, 23 plots in MHB, and 34 plots in DC (Figure 1). All plots were georeferenced using a Global Positioning System receiver. This methodology establishes two concentric circular subplots within each plot (Figure 3), where the minimum diameter threshold for recording woody individuals varies by ecoregion (Table S1). For each individual, structural variables were measured, including diameter at breast height (DBH), diameter at base height (DB), total height, and canopy metrics. Following the methodological and conceptual guidelines of the Second National Native Forest Inventory of Argentina [34], tree regeneration was quantified as the density of saplings (young woody individuals per hectare), based on diameter and height classes defined for each ecoregion.

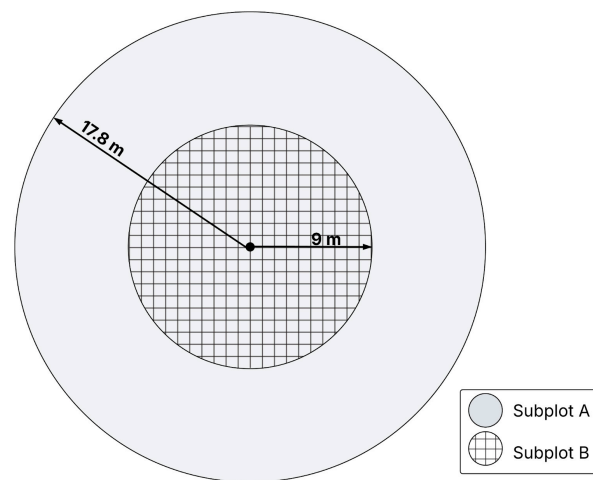


Figure 3. Diagram of the concentric circular subplot (A and B) used for field sampling of the different forest attributes.

To assess potential forest degradation, allometric equations were applied to field data to estimate the mean above-ground biomass (AGB) for each plot. AGB represents the dry matter weight of woody vegetation per unit area (e.g., tons $\times$ ha⁻¹) and serves as a key indicator of forest structure [35]. In the ecoregions assessed, each individual exhibits different morphological characteristics, and they branch out at different individual heights. The equations proposed by [36] were applied, due to these taking into account the bioform of woody individuals. Depending on the morphological characteristics of each woody individual, the most appropriate model was selected:

- For single-stemmed woody individuals, measured both at base height (0.1 m) and at breast height (1.3 m), the model of [37] was applied (Equation (1)):

$$AGB = 0.0673 (\rho \times DBH^2 \times H)^{0.976} \quad (1)$$

where ρ is the wood density (g/cm³); DBH is the diameter at 1.3 m stem height, and H is the tree height.

- For individuals with a single stem at the base that branches into multiple stems above 1.3 m height, Model 1 of [36] was used (Equation (2)):

$$AGB = e^{-2.281+1.525 \ln BD+0.831 \ln CD+0.523 \ln H} \quad (2)$$

where BD is the basal diameter (0.1 m); CD is the mean crown diameter; and H is the tree height (m).

- For multi-stemmed individuals at both base and breast height, Model 4 from [36] was applied (Equation (3)):

$$AGB = e^{-0.37+1.903 \ln CD+0.652 \ln H} \times 1.403 \quad (3)$$

Wood density values were determined for each species surveyed in the field using the available bibliographic sources for the study area. When specific local information was unavailable, data from reports for other Argentine regions were used. For species lacking national records, data were obtained from the INTI-CITEMA database [38]. If no species-level information was found, the mean wood density of the dataset was applied.

For each plot, the average AGB was estimated by applying the selected allometric equations to the woody individuals recorded. Likewise, the abundance density of juvenile individuals corresponding to each sampling unit was quantified. This variable extraction per plot was related to the following remote sensing data.

2.2.2. Spectral Proxies from Remote Sensing Data

Landsat 8 OLI Level-2 collection (30 m spatial resolution) was processed using Google Earth Engine (GEE; [39]). All Landsat images were processed in their native projection (UTM, WGS84, Zone 19S; EPSG:32619). Cloud, cirrus, and shadow pixels were removed by applying a bitwise mask to exclude contaminated observations. After filtering, a median composite was generated for the wet season (December 2022 to March 2023). This period corresponded to the highest vegetation growth and vigor, providing a stronger spectral response, and it coincided with the timing of the field survey.

From the Landsat 8 OLI collection, green band (0.53–0.59 μm) and several vegetation indices (VIs) were derived. Although the Normalized Difference Vegetation Index (NDVI) is widely used, it performs poorly in dry forest environments due to soil brightness effects and the limited sensitivity to senescent vegetation [40]. Therefore, alternative VIs better suited for dry forest monitoring were considered [41–43]. Among them were the Enhanced Vegetation Index (EVI) [44,45], which is sensitive to canopy structure variations such as leaf area index and vegetation physiognomy [44]; the Soil-Adjusted Vegetation Index (SAVI) [46], which reduces soil brightness in areas with sparse vegetative cover; and the Soil-Adjusted Total Vegetation Index (SATVI) [47], which is sensitive to both green and senescent vegetation. For both SATVI and SAVI, the adjusted soil parameters were $L = 0.5$ for intermediate vegetation densities present in the study area.

Additionally, Tasseled Cap Transformation (TCT) indices were calculated [48,49] by summing the products of the original spectral bands with specific coefficients (view Table S2 for specific information) to generate new composite bands, thereby enhancing the visualization of particular features in the imagery. The first Tasseled Cap index, the Brightness Index, represents soil reflectance; the second, the Greenness Index (GI), captures vegetation characteristics; and the third, the Wetness Index (WI), reflects the interaction between soil and vegetation. In this study, GI and WI were used as predictor variables for modeling forest attributes.

Field data were used to calibrate structural relationships between forest attributes and spectral metrics, which were then applied retrospectively to historical imagery following a space-for-time substitution approach. For each field plot, the geographic coordinates of the plot center were used to identify the corresponding reference pixel in the satellite image. A square neighborhood of 3×3 pixels (i.e., the reference pixel plus its eight immediate neighbors) was then defined around this location. Furthermore, the same 3×3 windowing procedure is repeated independently for each plot, which is why this technique is commonly referred to as a “moving window” in remote sensing applications. The purpose of using a local neighborhood instead of a single pixel is to (i) account for geolocation uncertainty

between field plots and satellite imagery, (ii) reduce within-pixel noise and mixed-pixel effects, and (iii) obtain a more stable representation of vegetation conditions at the scale of the plot [50]. For each plot-specific window, the median ($_m$) and standard deviation ($_sd$) of the spectral index were calculated. The median was selected because it is robust to outliers and local heterogeneity in mixed landscapes. The standard deviation represents the local spatial variability within the plot area.

2.2.3. Modeling Dry Forest Attributes (AGB and Tree Regeneration)

All predictor variables were standardized using z-scores before model fitting. Multicollinearity between the different variables used was assessed. Variables with multicollinearity $r > |0.8|$ were discarded and not included in the model. Then, Generalized Linear Mixed Models (GLMM) were fitted because our data exhibit a hierarchical structure and because the response variables (AGB and tree regeneration) follow non-Gaussian distributions [51,52]. The ecoregion (i.e., MHB, MPP, DC) was considered as a random effect, and spectral variables, without correlated variables, were included as fixed effects. The response variable AGB was log-transformed for the GLMM adjustment. Because models with tree regeneration as the response variable exhibited overdispersion, a negative binomial distribution was fitted, which is more appropriate [52]. All statistical analysis was executed by RStudio version 4.5.2 (31 October 2025).

Model selection was based on the information-theoretic approach [53], using the second-order Akaike Information Criterion (AIC). Specifically, Akaike's Information Criterion corrected for small sample size (AICc) was calculated for each model. Models were then compared using $\Delta AICc$, defined as the difference between the lowest AICc (i.e., the best-fitting model) and the AICc values of all other models. In addition, 95% confidence intervals (CL) were calculated for all parameter estimates. For all models, the R^2 conditional was determined and represents the proportion of variance explained by the model when both fixed effects and the hierarchical random effects are taken into account. Model performance was further assessed using the Likelihood Ratio Test (LRT) to identify the most accurate predictor spectral variable.

2.2.4. Temporal Dynamics and Breakpoints Detection (1993–2023)

To identify critical points in the AGB–precipitation and tree regeneration–precipitation relationships, and to assess temporal trends over the period analyzed (1993–2023), the TSS-RESTREND [24] methodology was applied. A monthly time series of the best-performing spectral proxy, the median TCTW for AGB and median EVI for tree regeneration, in each ecoregion was constructed using corresponding bands of Landsat 5 TM-Level 2 and Landsat 8 OLI-Level 2 (Table S2), both obtained from GEE. These collections contain atmospherically corrected surface reflectance and land surface temperature derived from the data produced by the Landsat TM sensor with the Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS) algorithm and the Land Surface Reflectance Code (LaSRC) for the OLI/TIRS sensors. Cloud, cirrus, and shadow pixels were removed for both collections by applying a bitwise mask to exclude contaminated observations. From these collections for each plot, the monthly median and standard deviation of VI values were calculated for the period 1993–2023 using indices that best represented AGB (TCTW median) and tree regeneration (EVI median), respectively. A temporal gap exists between the availability of images in Landsat 5, finished in November 2011, and Landsat 8, started in March 2013. To address this discontinuity, missing values were imputed using the “imputeTS” package in R [54], which provides algorithms for univariate time series imputation. Specifically, the seasonally split imputation method was applied, which divides the time series into seasonal

subsets and performs imputation independently within each subset, thereby preserving seasonal patterns and variability.

Different coefficients are used to calculate TCTW depending on the satellite used. For Landsat 8, the coefficients are specified in Table S2. For Landsat 5, the coefficients used are 0.0315, 0.2021, 0.3102, 0.1594, -0.6806 and -0.6109 for blue, green, red, NIR, SWIR1 and SWIR2 bands, respectively. Median and standard deviation values of the selected VIs (1993–2023) were calculated for each 3×3 pixel moving window, centered on the pixel corresponding to the study plot (reference pixel). Each pixel within the window was successively treated as the reference pixel to compute the median and standard deviation. Finally, the monthly median across all plots was averaged within each ecoregion.

2.2.5. Precipitation and TSS-RESTREND Analysis

Monthly precipitation data were obtained from TerraClimate in the GEE platform, which integrates WorldClim high-resolution climatological normal data with the coarser spatial resolution of time-varying data from CRU and JRA55 [55], currently ranging from 1958 to the present. For each plot, monthly cumulative precipitation was extracted for 1991–2023, and ecoregion medians were computed. Precipitation records from 1991 were used to compute accumulated rainfall with variable accumulation (1–24 months) and offset periods (0–3 months), following the TSS-RESTREND framework [24], in order to avoid truncation effects at the start of the VI time series.

The influence of precipitation on vegetation dynamics was assessed using the TSS-RESTREND framework [24], which combines regression analysis and structural break detection. An Ordinary Least Square (OLS) regression was applied to model the relationship between the complete time series of VIs (CTSR.VI) and the complete time series of optimal accumulated precipitation for each pixel during 1993–2023 (hereafter referred to as the vegetation–precipitation relationship, VPR). The optimal accumulated precipitation was determined by identifying the CTSR.VI–precipitation pairs that yielded the highest correlation coefficient. To this end, all possible OLS relationships between CTSR.VI and a matrix of precipitation accumulation periods (1–12 months) combined with offset periods (0–3 months) were evaluated. The relationships with the strongest correlations were then used to compute the residuals between observed and predicted CTSR.VI (hereafter VPR residuals).

The influence of precipitation on vegetation dynamics was assessed using the TSS-RESTREND framework, which combines regression analysis and structural break detection. For each ecoregion, VI anomalies were regressed against cumulative annual precipitation to estimate the VPR.

The BFAST method was applied to the VPR residuals to list potential breakpoints. The list of potential breakpoints was further evaluated for their significance in the VPR using the Chow test. Depending on the significance level of this test, several scenarios may arise (Figure S1):

- 1 If the breakpoint is not significant in the VPR residuals ($\alpha > 0.05$), RESTREND is performed on the entire residual series (simple RESTREND) (Equation (4)).

$$y_i = \beta_0 + \beta_1 x \quad (4)$$

where β_0 is the intercept, β_1 is the slope, and x is the year.

- 2 If the breakpoint is significant in the VPR residuals ($\alpha < 0.05$), its significance in the VPR itself is further evaluated using the Chow test.
 - 2a If the breakpoint is not significant in the VPR ($\alpha > 0.05$), the VPR is recalculated before and after the breakpoint (segmented VPR). RESTREND is then

applied to each new segment of the VPR residuals (segmented RESTREND) (Equation (5)).

$$y_i = \beta_0 + \beta_1 x_i + \beta_2 z_i + \beta_3 x_i z_i \quad (5)$$

where β_0 is the intercept, x is the year, z is the value of the dummy variable (0 or 1), β_1 is the slope, β_2 is the offset at the breakpoint, and β_3 is the change in the slope at the breakpoint.

- 2b If the breakpoint is significant in the VPR ($\alpha < 0.05$), RESTREND is applied to each new segment of the VPR residuals (segmented RESTREND). This significance indicates the presence of significant structural changes.

To allow the comparison of different accumulation and offset periods across the breakpoint, the optimal precipitation was converted into a standardized score (Equation (6)):

$$z_i = \frac{(x_i - \mu)}{\sigma} \quad (6)$$

where z_i is the standard score, x_i is the observed precipitation value, μ is the mean, and σ is the standard deviation of the accumulation period for the entire time series.

The VI and standard score time series were further evaluated by fitting a multivariate regression (Equation (7)):

$$Y_i = \beta_0 + \beta_1 x_i + \beta_2 z_i + \beta_3 x_i z_i \quad (7)$$

where x is the standardized precipitation for year i , z the value of the dummy variable (0 or 1), β_0 is the intercept, β_1 is the slope, β_2 is the offset at the breakpoint, and β_3 is the change in the slope at the breakpoint.

All statistical analyses and figures were performed in R (R Core Team, 2019) using the following packages: “tidyverse” [56], “corrplot” [57], “lme4” [58], “MuMIn” [59], “MASS” [60], “aod” [61] and “TSS.RESTREND” [62].

2.2.6. Spatial Mapping of Forest Attributes

To map the spatial patterns of changes in tree regeneration, we used Landsat imagery to compute annual median EVI values for selected periods. For MPP and MHB, Landsat 5 collections of GEE were used to calculate annual median EVI for 1997 and 1999, pre- and post-identified breakpoint (1998). The difference between these two layers was then computed to estimate EVI change and to spatially identify areas exhibiting potential tree regeneration loss. For DC, Landsat 8 data were used to derive the annual median EVI for 2011 and 2014. Although a breakpoint was detected in 2012, data from 2012 and 2013 were unavailable; therefore, these surrounding years were selected to capture pre- and post-breakpoint. The resulting EVI difference maps allowed the identification of spatial patterns of tree regeneration decline.

3. Results

3.1. Remote Sensing Proxies for Dry Forest Attributes

Before model fitting variables, the median and standard deviation of TCTG and SATVI were excluded due to a high multicollinearity ($r > |0.8|$). Several models based on GLMM were developed to identify the most effective proxies for assessing AGB and tree regeneration in dry forests. For AGB, the model with the lowest AIC included the green band (median and standard deviation) and the TCT Wetness component (median and standard deviation) (Table 1). The first model was selected based on AIC, retaining the model with the minimum value as the most efficient representation of the data. Subsequently, the confidence intervals of each predictor were examined to assess their statistical relevance.

Variables whose 95% confidence intervals included zero were considered non-significant and therefore excluded from the final model. Green_sd and TCTW_m were significant confidence intervals (Green_sd: [−2.58, −0.01]; TCTW_m: [0.05, 2.68]; Table S4). A new model was then fitted including only the significant predictors. The best-fitting model retained the standard deviation of the green band and the TCTW median as explanatory variables (Table S4), yielding a conditional R^2 of 0.413. To assess the significance of the fixed effects to identify just one spectral variable, the models were compared using the LRT (Table S5). The median TCTW was identified as the best predictor of AGB ($p = 0.034$).

Table 1. Selected generalized linear mixed models explaining AGB.

Model	AICc	Δ AICc	R^2 c
AGB ~ Green_m + Green_sd + TCTW_m + TCTW_sd	223.4	0.00	0.299
AGB ~ Green_m + Green_sd + TCTW_m	223.7	0.29	0.316
AGB ~ EVI_m + Green_m + Green_sd + TCTW_m + TCTW_sd	224	0.68	0.306
AGB ~ EVI_sd + Green_m + Green_sd + TCTW_m + TCTW_sd	224.3	0.96	0.294
AGB ~ EVI_m + Green_m + Green_sd + TCTW_m	224.6	1.24	0.312

AICc: corrected Akaike Information Criterion; Δ AICc: difference in AICc. “_m”: median; “_sd”: standard deviation; R^2 c: R^2 conditional.

Among the variables used to estimate tree regeneration, the model with the lowest AIC included the median EVI as the most effective predictor (Table 2). The confidence intervals of each predictor were examined to assess their statistical relevance. Variables whose 95% confidence intervals included zero were considered non-significant and were therefore excluded from the final model. Indeed, the spectral variable EVI_m has significant confidence intervals (1.07, 4.07; Table S6). The median EVI remained the most reliable spectral proxy for tree regeneration.

Table 2. Summary of the selected generalized linear mixed models explaining tree regeneration.

Model	AICc	Δ AICc	R^2 c
Reg ~ EVI_m	1094.5	0.00	0.172
Reg ~ EVI_m + Green_sd	1094.9	0.39	0.172
Reg ~ EVI_m + EVI_sd	1095.6	1.05	0.194
Reg ~ EVI_m + Green_sd + TCTW_m	1096.0	1.5	0.195
Reg ~ EVI_m + TCTW_m	1096.1	1.59	0.168

AICc: corrected Akaike Information Criterion. Δ AICc: difference in AICc. “_m”: median. “_sd”: standard deviation. R^2 c: R^2 conditional.

3.2. Temporal Dynamics and Breakpoints (1993–2023)

The temporal trends of the median TCTW (the proxy for AGB) revealed no breakpoint years across ecoregions. For DC and MPP, three different breakpoint years were found (1998, 2009 and 2012) using BFAST. However, all breakpoint years were not significant according to the Chow test (p -value = 0.2393 in DC; p -value = 0.0578 in MPP) for VPR. In MHB, four breakpoint years were detected using BFAST (1997, 2000, 2011 and 2015). Using the Chow test on VPR, these breakpoint years were not significant (p -value = 0.2181). No abrupt changes or breakpoint years were detected in AGB across the analyzed ecoregions (Figure 4). Furthermore, no pronounced temporal trend was exhibited. However, the MHB and DC ecoregions showed a slightly negative slope. A gradual decline in the seasonal variability of AGB was observed through time, coinciding with a reduction in monthly precipitation over the past decade.

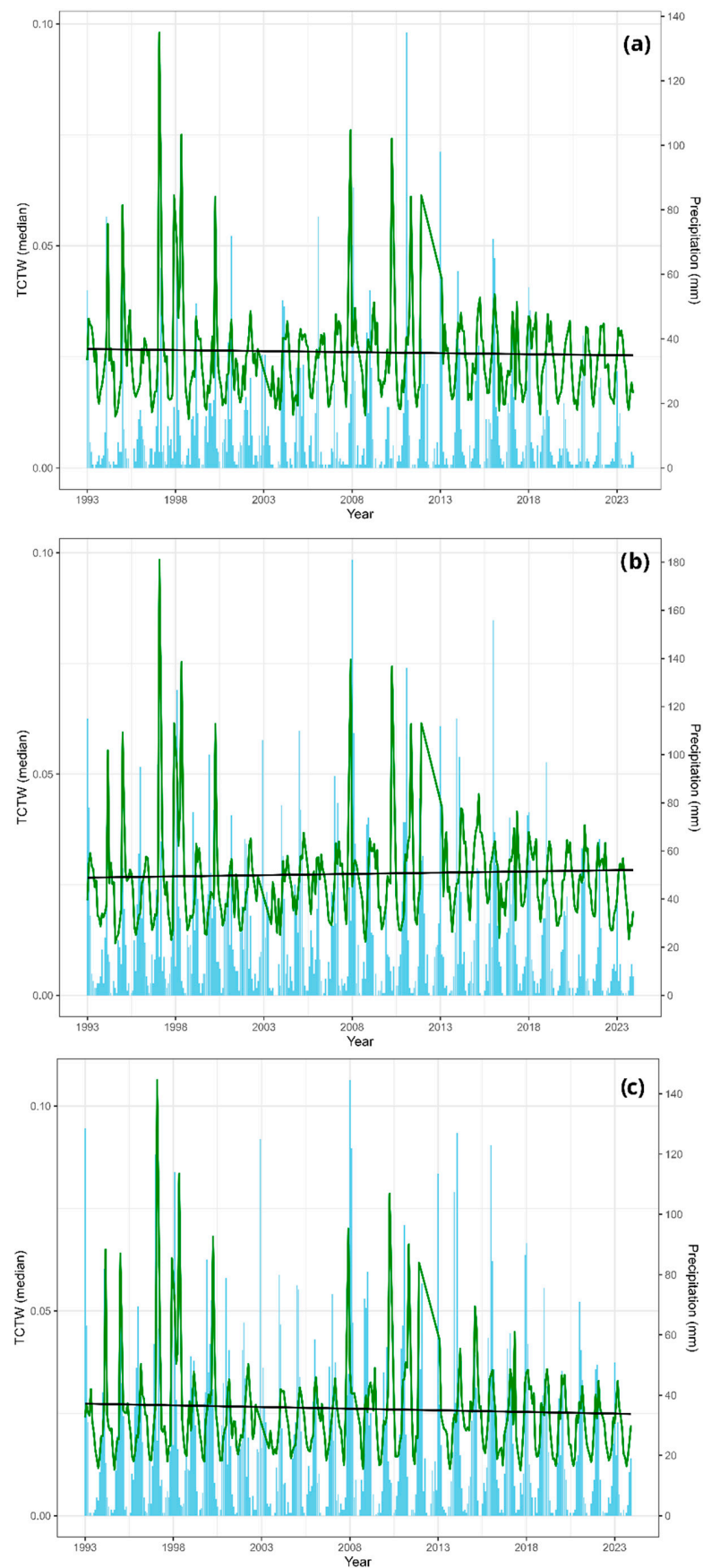


Figure 4. Temporal variation in the median Tasseled Cap Transformation Wetness (TCTW; green line) and monthly precipitation (light blue bars) from 1993 to 2023 across the three studied ecoregions: (a) Monte of Hills and Basin, (b) Monte of Plains and Plateaus, and (c) Dry Chaco.

In contrast, the median EVI, used as a proxy for tree regeneration, revealed different temporal patterns among ecoregions. Breakpoint years were found using BFAST in MHB (1996, 1998, 2008, 2010 and 2013). However, the Chow test determined 1998 as a significant year for VPR (p -value = 0.0181; F = 4.665) (Figure 5a). Similar breakpoint years (1998, 2010 and 2013) were determined for the MPP using BFAST, but only 1998 was a significant year according to the Chow test (p -value = 0.0226; F = 4.3727) for VPR (Figure 6a). A positive tree regeneration trend was observed between 1993 and 1997 (Figures 5a and 6a), followed by an abrupt decline in 1998 in MHB and MPP. After this breakpoint, tree regeneration gradually recovered, exhibiting an increasing trend that eventually returned to pre-decline levels.

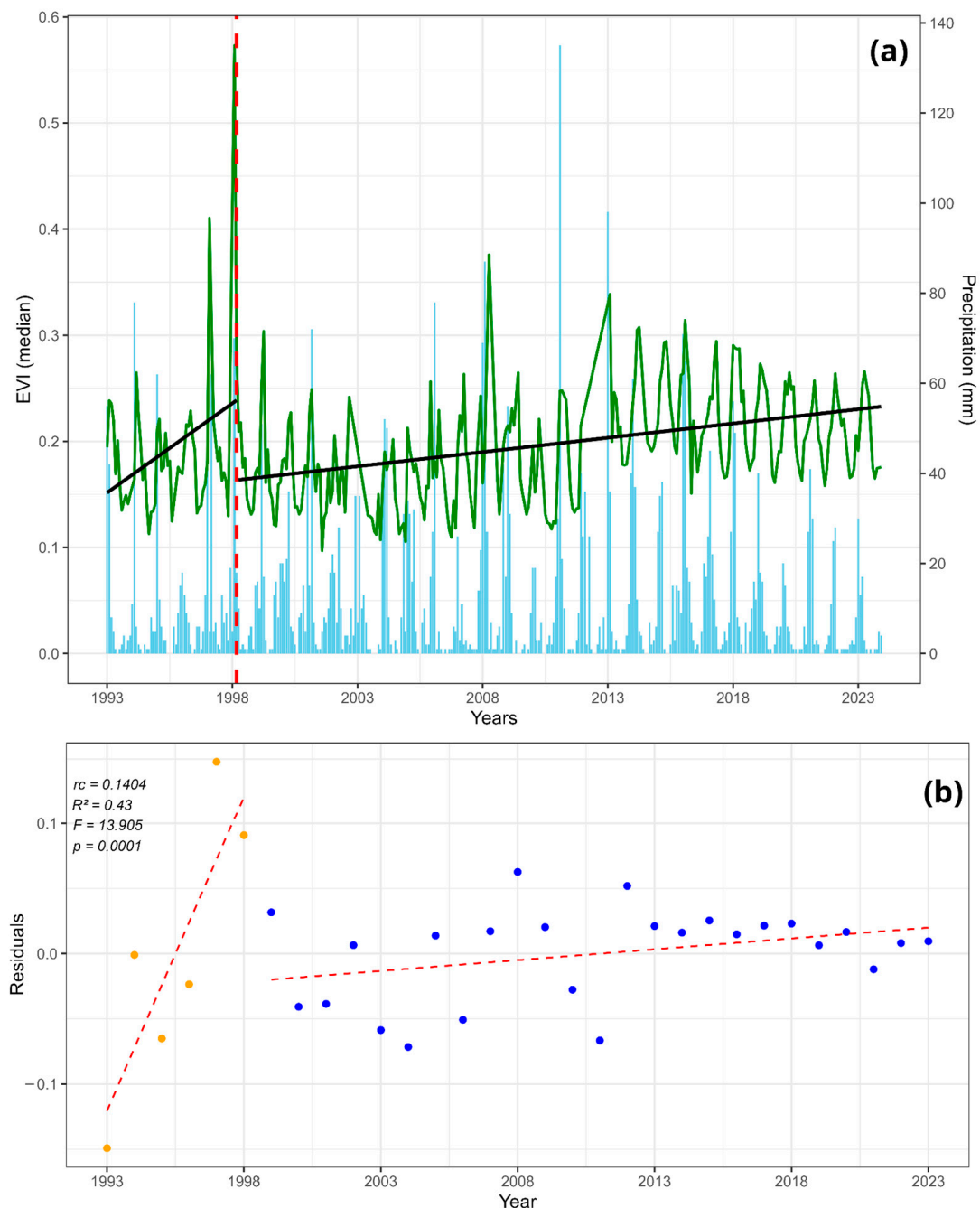


Figure 5. Median Enhanced Vegetation Index (EVI) time series (1993–2023) for the Monte of Hills and Basin ecoregion. (a) Temporal variation in median EVI (green line), breakpoint year (dashed red line), and monthly precipitation (light blue bars). (b) RESTREND before and after the most significant breakpoint (year = 1998) identified using the Chow test. Points represent total yearly changes in VPR (vegetation–precipitation relationship) residuals before (orange) and after (blue) the breakpoint year.

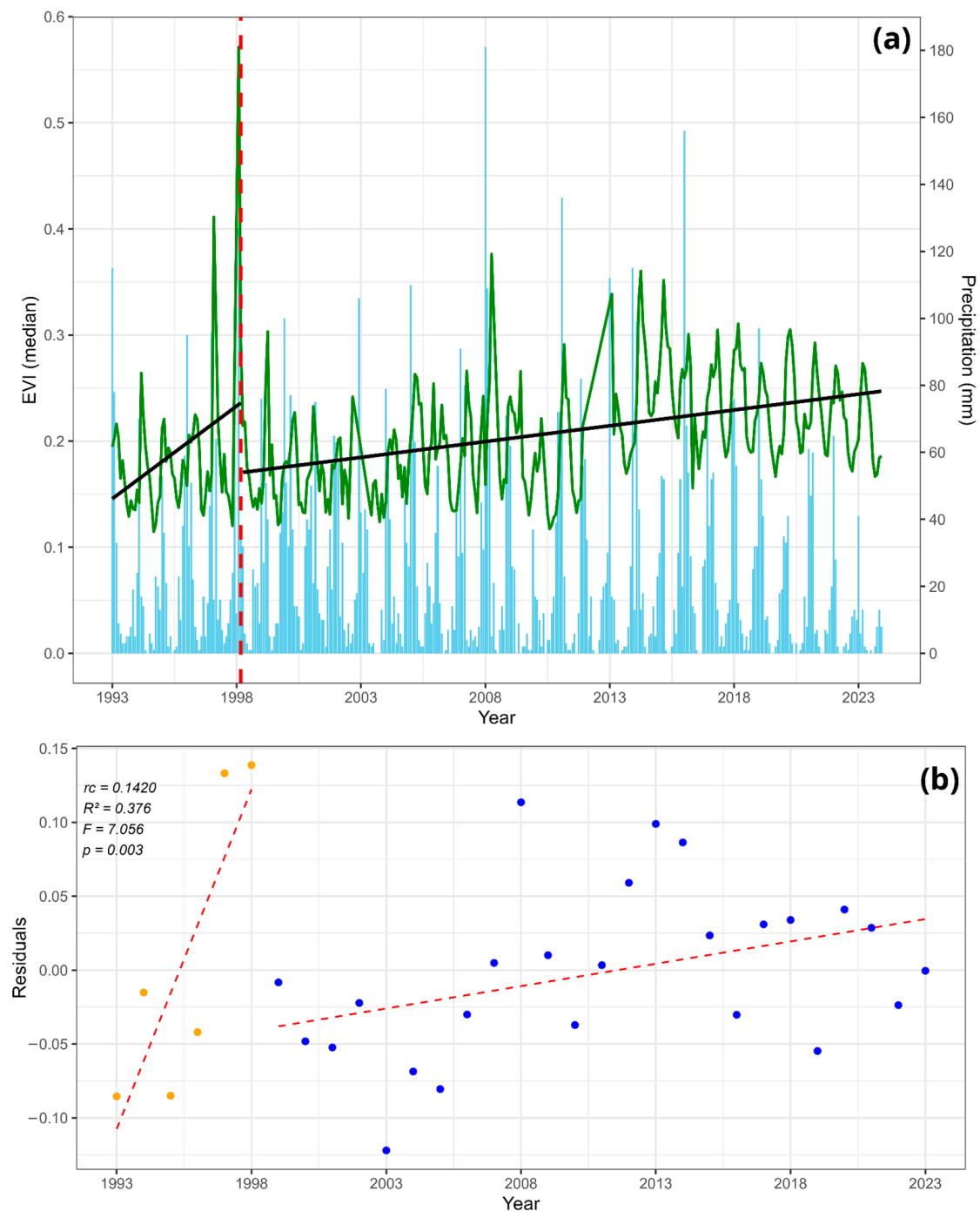


Figure 6. Median Enhanced Vegetation Index (EVI) time series (1993–2023) for the Monte of Plains and Plateau ecoregion. **(a)** Temporal variation in median EVI (green line), breakpoint year (dashed red line), and monthly precipitation (light blue bars). **(b)** RESTREND before and after the most significant breakpoint (year = 1998) identified using the Chow test. Points represent total yearly changes in VPR (vegetation–precipitation relationship) residuals before (orange) and after (blue) the breakpoint year.

In the DC ecoregion, 1998, 2008 and 2012 were identified as breakpoint years using BFAST for the median EVI, but only 2013 was a significant year according to the Chow test (p -value < 0.001, $F = 9.7451$) for VPR. A slight positive trend from 1993 to 2012 (Figure 7) displays a statistically significant breakpoint in 2013. In the subsequent decade (2013–2023), it remained above pre-breakpoint levels but shifted toward a negative trend, coinciding with a marked decrease in precipitation during the last six years of the study.

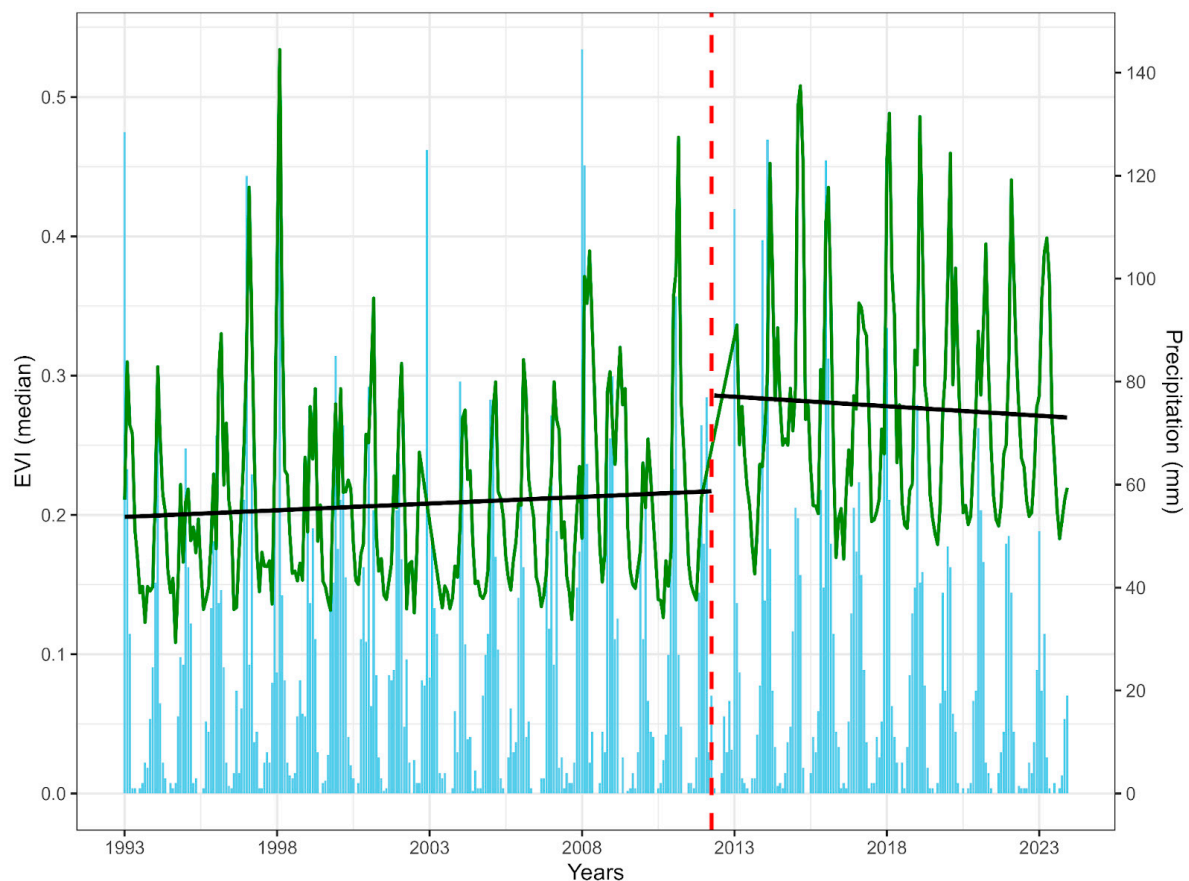


Figure 7. Median Enhanced Vegetation Index (EVI) time series (green lines) (1993–2023) for the Dry Chaco ecoregion. Breakpoint year = dashed red line; year = 2012. Monthly precipitation = light blue bars.

3.3. Relationship Between Precipitation and Forest Attributes

Using residual analysis, TSS-RESTREND allows the assessment of whether structured information remains after modeling time series with climatic variables. In the MPP and MHB, the residuals showed a positive trend between 1993 and 1997 (Figures 5b and 6b), indicating improvements in the median EVI beyond what would be expected from precipitation alone. However, this period was relatively short, limiting the robustness of the trend. The Chow test identified 1998 as a significant breakpoint year in VPR residuals (in MPP, p -value = 0.0034, F = 7.056) (in MHB, p -value < 0.001; F = 13.905) (Figures 5b and 6b). After the 1999 breakpoint, a weak positive residual trend persisted, suggesting that factors may have contributed to tree regeneration dynamics independent of precipitation. In contrast, Chow's test indicated that VPR residuals in DC were not statistically significant, suggesting that temporal variations in the median EVI were largely explained by precipitation variability, with no evidence of an independent or sustained trend.

3.4. Spatial Distribution of AGB and Tree Regeneration

In DC, the median EVI increased slightly between 2011 and 2014 across most of the area (Figure 8), particularly along hydrological networks. Spatial comparisons between 1997 and 1999 (Figure 9) highlight a clear contrast before and after the main breakpoint. In MHB, declines were evident along the mountain range bordering DC and the southern riverbeds. In MPP, lower values were observed in the southwest sector and along riverbeds.

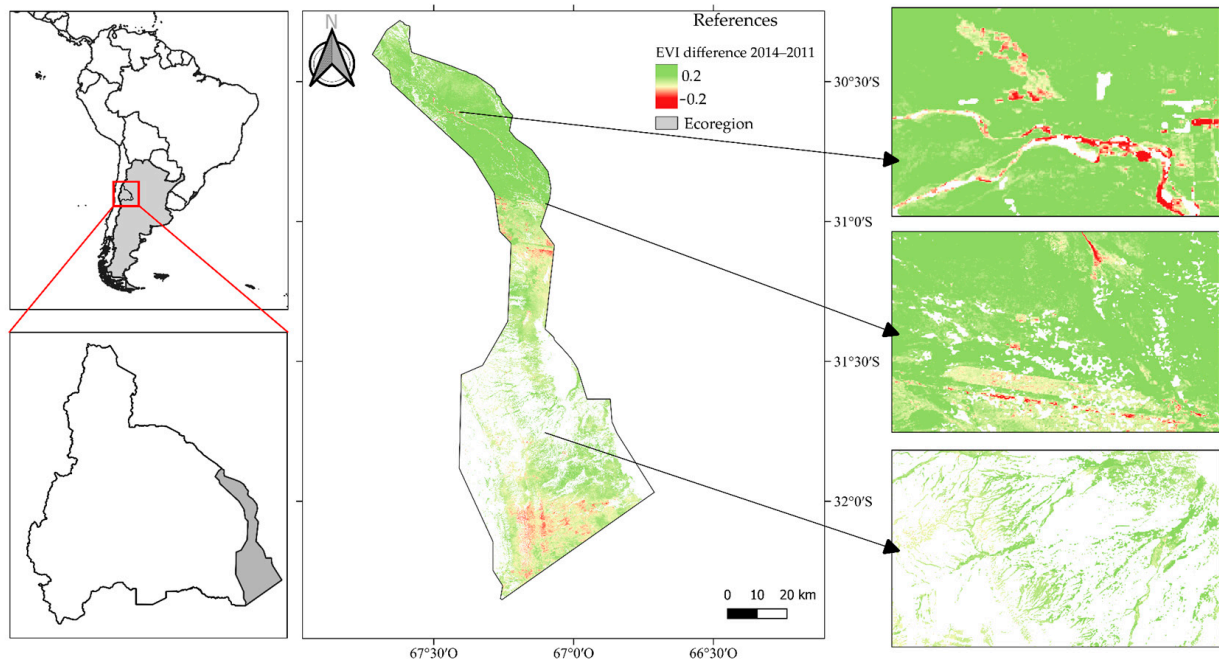


Figure 8. Difference in median EVI values between 2011 and 2014 for Dry Chaco (breakpoint year = 2012). Green areas indicate positive differences; yellow to red areas indicate negative differences; white areas represent non-forest regions.

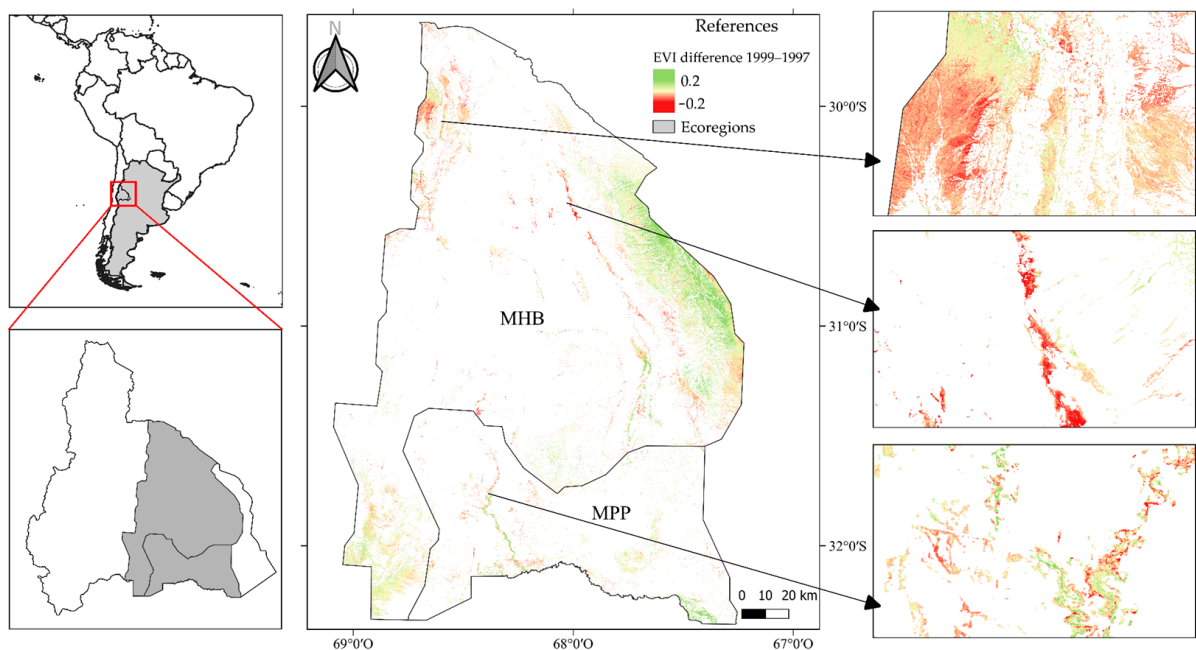


Figure 9. Difference in median EVI values between 1997 and 1999 (breakpoint year = 1998) for Monte of Hills and Basin and Monte of Plains and Plateaus. Green areas indicate positive differences within the ecoregion; yellow to red areas indicate negative differences; white areas represent non-forest regions.

4. Discussion

In this study, remote sensing and field measurements were integrated to evaluate dry forest degradation across multiple regions over three decades. Efficient remote sensing indicators (i.e., proxies) were identified for monitoring forest attributes. Median TCT Wetness was the best proxy for AGB and the median EVI for tree regeneration. From 1993 to 2023, the temporal dynamics of these proxies varied among regions: the median TCTW

slightly declined in Dry Chaco and MHB but increased in MPP, while the median EVI showed a greater variability. A breakpoint in 1998 marked a decline in EVI in the driest regions (MHB and MPP), especially near watercourses, whereas tree regeneration increased in Dry Chaco after 2013, coinciding with lower precipitation. Although precipitation remains a major driver of dry forest dynamics, the findings suggest a weakening in the strength of the relationship between forest attributes and precipitation.

4.1. Best-Performing Spectral Proxy

The results show that the median TCT Wetness and the standard deviation of the green band together explained 41% of the AGB variability based on field data. This level of explained variance is noteworthy, considering the multiple factors influencing biomass (e.g., woody species composition, stand structure, life forms, water absorption, anthropogenic activities, and sensor spatial resolution). In dry forests, where water availability is the dominant control, TCTW is closely linked to vegetation structure, forest maturity [63,64], canopy density, and leaf water content, all of which scale with tree biomass [65]. Areas with higher values typically display a greater structural complexity, reflected in the higher spectral variability. This pattern is consistent with findings from other dry and semi-arid forests, where spectral heterogeneity and moisture-sensitive indices are reliable predictors of biomass (e.g., [66,67]). There are few studies in which TCTW is used as a proxy of any forest attributes. In Upper Forest Guinea, TCTW was identified as a predictor of woody vegetation cover [68] in forests with a rainfall regime that exceeds that of the study area in this work (<1200 mm). No studies have determined TCTW as a predictor of AGB in dry forests. This scarcity of previous studies underscores the contribution of the present work by providing new empirical evidence on the applicability of TCTW for AGB estimation in dry forests. Other popular vegetation indices have also been applied to estimate AGB across different environments, such as NDVI or NDMI in subtropical dry forests [69] or SAVI in the Caatinga forest [70]. Although airborne remote sensing provides a higher accuracy, its high cost and limited cover constrain its operational use. Thus, Landsat and Sentinel imagery remain the most accessible and effective alternatives for large-scale AGB estimation in South America [71].

Tree regeneration was also successfully modeled using another forest attribute estimated from spectral variables. Among the tested indices, the median EVI performed best, explaining 25% of the variability. In a similar area, the abundance of *N. flexuosa* saplings has been positively related to TCT Brightness and negatively to TCT Wetness [72]. In a tropical forest in Uganda after recovery interventions, EVI and NDVI values increased over time, but non-linear patterns of regeneration were observed across the first 25 years of recovery [73]. The evaluation of natural regeneration in dry forests using remote sensing is an under-explored area. However, it is well known that EVI effectively captures canopy structural variations and plant physiognomy [44], enhancing the detection of subtle vegetation changes while minimizing soil and atmospheric effects. Higher values largely reflect canopy-level processes, such as water use, evapotranspiration, and canopy conductance, which regulate carbon and water fluxes [74]. The observed correlation between the EVI and tree regeneration likely reflects the role of mature trees in shaping favorable microhabitats for sapling establishment [72]. However, tree regeneration models exhibited a modest explanatory power, reflecting the inherently stochastic nature of recruitment processes in dry forests and the limitations of moderate-resolution remote sensing. Tree regeneration is also influenced by factors beyond canopy dynamics, such as forest edges, landscape connectivity, soil disturbance, and biotic interactions [75]. Despite its central role in forest persistence, particularly in slow-growing, stress-sensitive dry forests, the linkage between tree regeneration and spectral indices remains poorly understood.

4.2. Spatial-Temporal Variability of Forest Attributes

AGB revealed no abrupt changes or major breakpoints, although the slight negative trend detected in the MHB and DC ecoregions suggests a gradual, long-term degradation in this attribute. Conversely, MPP exhibited a weak positive trajectory. Previous studies reported positive NDVI trends (as a proxy of forest productivity) in MHB between 2000 and 2014 [76] and across all three ecoregions at broader temporal scales. Similarly, drylands in Australia displayed an overall greening from 1982 to 2013, with only limited forest degradation [24]. In the present study, TCTW and precipitation declined over the studied period, while chronic anthropogenic pressures likely exacerbate this pattern, contributing to a persistent, small-scale degradation ecosystem condition [77,78].

Tree regeneration followed a different dynamic compared to AGB across ecoregions. In the Monte ecoregions (MHB and MPP), the median EVI exhibited a breakpoint in 1998, followed by a prolonged, slow recovery lasting two decades, eventually reaching pre-breakpoint levels and subsequently displaying a positive trend. This slow recovery likely reflects the intrinsic resilience of these forests through self-organization, allowing adaptations to structural changes [79], and the relatively low anthropogenic pressure in the study area. The post-breakpoint increase in tree regeneration was not directly linked to precipitation, whose seasonal variability decreased over time. Instead, other environmental drivers, such as temperature dynamics and alternative water sources like groundwater and meltwater [80,81] and hydrological processes such as runoff and evapotranspiration, may play a crucial role in sustaining tree regeneration in these ecosystems [82]. In contrast, Dry Chaco showed a positive tree regeneration trend from 1993 to 2012, followed by a marked increase after 2013. This pattern is consistent with global dryland greening, attributed mainly to CO₂ fertilization and, to a lesser extent, nitrogen deposition, climate change, and land cover change [8,77]. Similar trends have been documented in other arid regions, including China [83], South Africa [84], and Australia [85]. However, after the 2013 breakpoint, tree regeneration in Dry Chaco exhibited a slight negative trend over time, consistent with the regional EVI declines reported between 2000–2014 [86]. This could be associated with non-climatic drivers such as water deficit and land use pressures. Also, the time lag of seed germination and establishment in dry forests is another factor influenced by precipitation and infiltration [87]. Nevertheless, given that only 12 years have elapsed since the 2013 breakpoint, longer-term data are needed to fully understand the dynamics of tree regeneration and the drivers of these changes.

Across all ecoregions, an anomalously high spike is observed around 1998, standing out relative to the rest of the time series and therefore requiring cautious interpretation, as its underlying cause cannot be determined with certainty. This anomaly may influence breakpoint detection and the estimation of apparent temporal trends. The cause of this spike could be caused by different large-scale phenomena (climatic variability, extreme wet and dry years, El Niño and La Niña) that affected drylands and their response in time. For example, an excessive increase in rainfall was observed in the Austral Chaco region in 1998 due to an El Niño event [88], and, in contrast, an extreme drought was identified in Chile in the same year [89]. In addition, potential sensor-related influences on the detected temporal trends and breakpoints in the median EVI were considered. Transitions within the Landsat program around 1998 and 2013 could, in principle, introduce discontinuities in long-term vegetation index time series. However, although some breakpoints temporally coincide with these sensor transitions, they are neither consistently detected across ecoregions nor synchronously distributed across the study area. The spatially heterogeneous timing of breakpoints therefore does not support sensor changes as the dominant driver of the observed temporal patterns.

Spatial variability in Dry Chaco revealed a general increase in AGB between 2011 and 2014, particularly associated with riparian catchments benefiting from greater soil moisture and sediment deposition, which support vegetation growth in dry forests. AGB declines were restricted to small, spatially discrete patches, associated with anthropogenic disturbances, such as deliberate burning for pasture establishment and livestock grazing [90]. In the Monte ecoregions (MHB and MPP), tree regeneration declines between 1997 and 1999 were most evident near watercourses, whereas localized recovery zones were detected in eastern MHB. This zone was characterized by the increased median EVI values after the breakpoint, suggesting localized vegetation recovery. In Dry Chaco, tree regeneration displayed a high spatial variability linked to interannual fluctuations in demographic processes (recruitment and mortality) driven by stochastic climatic events, such as droughts and favorable wet periods [90,91]. Overall, the interplay of hydrological processes, climatic variability, topographic conditions, and anthropogenic pressures emerges as a major driver of the pronounced spatial heterogeneity that characterizes arid and semi-arid ecosystems [31].

Although few studies have applied TSS-RESTREND specifically to dry forest ecosystems [24,92–94], the trends detected here are consistent with the broader patterns reported across global drylands. Several studies have documented a partial decoupling between precipitation and vegetation activity [95,96] under conditions of cumulative drought, groundwater depletion, or land use intensification, supporting the observation that precipitation alone cannot fully explain changes in tree regeneration or AGB. Likewise, the spectral variables identified as the most informative in models (particularly TCW and EVI) have repeatedly emerged as strong predictors of canopy moisture, woody cover, and tree regeneration in other dryland and tropical forest studies [97–99]. Finally, an El Niño event influenced South America in 1997–1998. This produced an anomaly effect in vegetation–precipitation dynamics [88,100]. These converging lines of evidence indicate that, despite methodological differences, the results are broadly consistent with those reported for similar ecosystems.

Several limitations and sources of uncertainty in the study design should be acknowledged. Field observations correspond only to the 2022–2023 period, and no multi-temporal field data are available to directly validate the long-term trends detected in the satellite time series at the plot scale. Moreover, sampling a larger number of plots allows us to capture the full range of these attributes, which would enable a better fit of the models than that obtained. This lack of historical in situ measurements limits the ability to precisely quantify the temporal magnitude of changes in attributes such as AGB and tree regeneration. Despite these limitations, the study provides robust and valuable evidence of persistent vegetation change by leveraging multi-decadal Landsat and TerraClimate datasets and applying the TSS-RESTREND framework, which is specifically designed to detect structural changes in vegetation–climate relationships. Moreover, few studies have applied this type of statistical framework to assess long-term vegetation dynamics, and even fewer have done so in the dryland ecosystems of Argentina, underscoring the novelty and relevance of the present contribution. These approaches enhance the robustness of persistent change detection but cannot substitute for multi-temporal field validation. Consequently, any attribution of the observed trends to anthropogenic processes (e.g., land use change, fire, or grazing) is presented here as hypothetical and discussed with caution. The results should thus be interpreted primarily as evidence of persistent vegetation change. Future research should incorporate multi-temporal field measurements, when available, and integrate land use change maps and high-resolution image series for more direct attribution.

5. Conclusions

This study explored the response and predictive capacity of passive remote sensing for monitoring key dry forest attributes, including above-ground biomass and tree regeneration, in west Argentina. Both attributes exhibited contrasting temporal and spatial patterns across ecoregions, reflecting the inherent heterogeneity of these ecosystems. The Tasseled Cap Transformation Wetness and Enhanced Vegetation Index proved valuable as large-scale, long-term proxies of dry forest dynamics, with 25% and 40% explanatory power of spectral indices with respect to field-based measurements. Tasseled Cap Wetness and EVI revealed contrasting long-term trajectories among regions between 1993 and 2023. Precipitation remained a major driver of forest dynamics, but the detected regional divergences—including a late-1990s shift in the driest areas and a recent increase in regeneration in the Dry Chaco despite a reduced rainfall—suggest that forest dynamics are becoming less tightly coupled to precipitation alone. This partial decoupling indicates the influence of additional factors such as topography and land use change. Overall, these findings underscore the importance of integrating long-term remote sensing time series with field-based observations and environmental variables to improve the accuracy and ecological relevance of forest monitoring in dryland regions. Future studies may integrate machine learning approaches to improve predictive performance. This integrative framework provides a valuable basis for detecting persistent structural changes, identifying tree regeneration and degradation hotspots, and supporting conservation and land management strategies aimed at enhancing ecosystem resilience under increasing climatic and anthropogenic pressures.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/land15020350/s1>, Table S1. Threshold values of diameter at breast height (DBH) and diameter at base (DB) used to classify individuals in the Dry Chaco and Monte ecoregions for sampling subplots A and B. Table S2. Spectral variables used in the study, with their corresponding calculation formulas for Landsat 8. Table S3. Descriptive statistics of above-ground biomass and tree regeneration for three ecoregions. Table S4. Confidence interval limits (CL; upper and lower) for spectral variables for AGB. Significant variables whose confidence intervals do not include zero are in bold (“_m”: median; “_sd”: standard deviation). Table S5. Comparison of models applying the Likelihood Ratio Test (LRT). LL: log-likelihood; k: number of parameters; AICc: corrected Akaike Information Criterion; Δ AICc: difference in AICc; *p*-value: LRT *p*-value significance; “_m”: median; “_sd”: standard deviation; R^2_c : R^2 conditional. Table S6. Confidence interval limits (CL, upper and lower) for the explanatory variables in tree regeneration models. Significant variables whose intervals do not include zero are in bold. Figure S1. Workflow of the TSS-RESTREND methodology applied here to detect breakpoints in the vegetation–precipitation (VPR) relationship (adapted from [101]).

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Abbreviations

The following abbreviations are used in this manuscript:

AGB	Above-Ground Biomass
AIC	Akaike Information Criterion
BFAST	Breaks for Additive Season and Trend
CL	Confidence Intervals
CTSR.VI	Complete Time Series of VIs
DC	Dry Chaco
EVI	Enhanced Vegetation Index
GEE	Google Earth Engine
GLMM	Generalized Linear Models Mixture
INTI-CITEMA	Instituto Nacional de Tecnología Industrial—Centro de Investigaciones y Desarrollo en Ciencias y Tecnología de Materiales
LAI	Leaf Area Index
LRT	Likelihood Ratio Test
MHB	Monte of Hills and Basins
MPP	Monte of Plains and Plateaus
NDVI	Normalized Difference Vegetation Index
OLS	Ordinary Least Square
SAR	Synthetic Aperture Radar
SATVI	Soil-Adjusted Total Vegetation Index
SAVI	Soil-Adjusted Vegetation Index
TCT	Tasseled Cap Transformation
TCTW	Tasseled Cap Transformation Wetness
TSS-RESTREND	Time Series Segmentation-RESidualTRENDS
VI	Vegetation Index
VPR	Vegetation–Precipitation Relationship

References

1. Gaur, M.K.; Squires, V.R. Geographic Extent and Characteristics of the World's Arid Zones and Their Peoples. In *Climate Variability Impacts on Land Use and Livelihoods in Drylands*; Springer International Publishing: Cham, Switzerland, 2018; pp. 3–20, ISBN 978-3-319-56681-8.
2. Prăvălie, R. Drylands Extent and Environmental Issues. A Global Approach. *Earth Sci. Rev.* **2016**, *161*, 259–278. [[CrossRef](#)]
3. Corvalán, C.; Hales, S.; McMichael, A.J.; Millennium Ecosystem Assessment; World Health Organization. *Ecosystems and Human Well-Being: Health Synthesis*; World Health Organization: Geneva, Switzerland, 2005.
4. Safriel, U.; Adeel, Z.; Niemeijer, D.; Puigdefabregas, J.; White, R.; Lal, R.; Winslow, M.; Ziedler, J.; Prince, S.; Archer, E.; et al. Dryland Systems. In *Ecosystems and Human Well-Being: Current State and Trends*; Island Press: Washington, DC, USA, 2005; pp. 623–662, ISBN 978-1-55963-228-7.
5. Huang, J.; Yu, H.; Guan, X.; Wang, G.; Guo, R. Accelerated Dryland Expansion under Climate Change. *Nat. Clim. Change* **2016**, *6*, 166–171. [[CrossRef](#)]
6. Wilkie, M.L.; Heymell, V. Hacia Una Definición de Degradación de Los Bosques: Análisis Comparativo de Las Definiciones Existentes. Roma (Italia), 8–10 Septiembre 2009. In *Programa de Evaluación de los Recursos Forestales. Documento de Trabajo* (FAO); FAO: Rome, Italy, 2009.

7. Simula, M.; Mansur, E. A Global Challenge Needing Local Response. *Unasylva* **2011**, *62*, 3–7.
8. Gonsamo, A.; Ciais, P.; Miralles, D.G.; Sitch, S.; Dorigo, W.; Lombardozzi, D.; Friedlingstein, P.; Nabel, J.E.M.S.; Goll, D.S.; O'Sullivan, M.; et al. Greening Drylands despite Warming Consistent with Carbon Dioxide Fertilization Effect. *Glob. Change Biol.* **2021**, *27*, 3336–3349. [[CrossRef](#)]
9. Brookshire, E.N.J.; Stoy, P.C.; Currey, B.; Finney, B. The Greening of the Northern Great Plains and Its Biogeochemical Precursors. *Glob. Change Biol.* **2020**, *26*, 5404–5413. [[CrossRef](#)]
10. Song, X.-P.; Hansen, M.C.; Stehman, S.V.; Potapov, P.V.; Tyukavina, A.; Vermote, E.F.; Townshend, J.R. Global Land Change from 1982 to 2016. *Nature* **2018**, *560*, 639–643. [[CrossRef](#)]
11. Noy-Meir, I. Desert Ecosystems: Environment and Producers. *Annu. Rev. Ecol. Syst.* **1973**, *4*, 25–51. [[CrossRef](#)]
12. Ukkola, A.M.; De Kauwe, M.G.; Roderick, M.L.; Burrell, A.; Lehmann, P.; Pitman, A.J. Annual Precipitation Explains Variability in Dryland Vegetation Greenness Globally but Not Locally. *Glob. Change Biol.* **2021**, *27*, 4367–4380. [[CrossRef](#)]
13. FAO (Food and Agriculture Organization of the United Nations). Assessing Forest Degradation—Towards the Development of Globally Applicable Guidelines. 2011. Available online: <https://restoration.elti.yale.edu/resource/assessing-forest-degradation-towards-development-globally-applicable-guidelines> (accessed on 12 February 2026).
14. Ghazoul, J.; Chazdon, R. Degradation and Recovery in Changing Forest Landscapes: A Multiscale Conceptual Framework. *Annu. Rev. Environ. Resour.* **2017**, *42*, 161–188. [[CrossRef](#)]
15. Vásquez-Grandón, A.; Donoso, P.J.; Gerding, V. Forest Degradation: When Is a Forest Degraded? *Forests* **2018**, *9*, 726. [[CrossRef](#)]
16. Jucker, T.; Caspersen, J.; Chave, J.; Antin, C.; Barbier, N.; Bongers, F.; Dalponte, M.; van Ewijk, K.Y.; Forrester, D.I.; Haeni, M.; et al. Allometric Equations for Integrating Remote Sensing Imagery into Forest Monitoring Programmes. *Glob. Change Biol.* **2017**, *23*, 177–190. [[CrossRef](#)]
17. Baumann, M.; Levers, C.; Macchi, L.; Bluhm, H.; Waske, B.; Gasparri, N.I.; Kuemmerle, T. Mapping Continuous Fields of Tree and Shrub Cover across the Gran Chaco Using Landsat 8 and Sentinel-1 Data. *Remote Sens. Environ.* **2018**, *216*, 201–211. [[CrossRef](#)]
18. Halperin, J.; LeMay, V.; Coops, N.; Verchot, L.; Marshall, P.; Lochhead, K. Canopy Cover Estimation in Miombo Woodlands of Zambia: Comparison of Landsat 8 OLI versus RapidEye Imagery Using Parametric, Nonparametric, and Semiparametric Methods. *Remote Sens. Environ.* **2016**, *179*, 170–182. [[CrossRef](#)]
19. Gao, Y.; Skutsch, M.; Paneque-Gálvez, J.; Ghilardi, A. Remote Sensing of Forest Degradation: A Review. *Environ. Res. Lett.* **2020**, *15*, 103001. [[CrossRef](#)]
20. Miettinen, J.; Stibig, H.-J.; Achard, F. Remote Sensing of Forest Degradation in Southeast Asia—Aiming for a Regional View through 5–30 m Satellite Data. *Glob. Ecol. Conserv.* **2014**, *2*, 24–36. [[CrossRef](#)]
21. Fremout, T.; Cobián-De Vinata, J.; Thomas, E.; Huaman-Zambrano, W.; Salazar-Villegas, M.; Limache-de la Fuente, D.; Bernardino, P.N.; Atkinson, R.; Csaplovics, E.; Muys, B. Site-Specific Scaling of Remote Sensing-Based Estimates of Woody Cover and Aboveground Biomass for Mapping Long-Term Tropical Dry Forest Degradation Status. *Remote Sens. Environ.* **2022**, *276*, 113040. [[CrossRef](#)]
22. Chen, Y.; Huang, X.; Huang, J.; Liu, S.; Lu, D.; Zhao, S. Fractional Monitoring of Desert Vegetation Degradation, Recovery, and Greening Using Optimized Multi-Endmembers Spectral Mixture Analysis in a Dryland Basin of Northwest China. *GIScience Remote Sens.* **2021**, *58*, 300–321. [[CrossRef](#)]
23. Chen, Z.; Liu, J.; Hou, X.; Fan, P.; Qian, Z.; Li, L.; Zhang, Z.; Feng, G.; Li, B.; Sun, G. Detection and Attribution of Greening and Land Degradation of Dryland Areas in China and America. *Remote Sens.* **2023**, *15*, 2688. [[CrossRef](#)]
24. Burrell, A.L.; Evans, J.P.; Liu, Y. Detecting Dryland Degradation Using Time Series Segmentation and Residual Trend Analysis (TSS-RESTREND). *Remote Sens. Environ.* **2017**, *197*, 43–57. [[CrossRef](#)]
25. Higginbottom, T.P.; Symeonakis, E.; Meyer, H.; van der Linden, S. Mapping Fractional Woody Cover in Semi-Arid Savannahs Using Multi-Seasonal Composites from Landsat Data. *ISPRS J. Photogramm. Remote Sens.* **2018**, *139*, 88–102. [[CrossRef](#)]
26. Wessels, K.J.; van den Bergh, F.; Scholes, R.J. Limits to Detectability of Land Degradation by Trend Analysis of Vegetation Index Data. *Remote Sens. Environ.* **2012**, *125*, 10–22. [[CrossRef](#)]
27. Kuenzer, C.; Dech, S.; Wagner, W. Remote Sensing Time Series Revealing Land Surface Dynamics: Status Quo and the Pathway Ahead. In *Remote Sensing Time Series: Revealing Land Surface Dynamics*; Kuenzer, C., Dech, S., Wagner, W., Eds.; Springer International Publishing: Cham, Switzerland, 2015; pp. 1–24, ISBN 978-3-319-15967-6.
28. Higginbottom, T.P.; Symeonakis, E. Assessing Land Degradation and Desertification Using Vegetation Index Data: Current Frameworks and Future Directions. *Remote Sens.* **2014**, *6*, 9552–9575. [[CrossRef](#)]
29. Verbesselt, J.; Hyndman, R.; Newnham, G.; Culvenor, D. Detecting Trend and Seasonal Changes in Satellite Image Time Series. *Remote Sens. Environ.* **2010**, *114*, 106–115. [[CrossRef](#)]
30. Labraga, J.C.; Villalba, R. Climate in the Monte Desert: Past Trends, Present Conditions, and Future Projections. *J. Arid Environ.* **2009**, *73*, 154–163. [[CrossRef](#)]
31. Bisigato, A.J.; Villagra, P.E.; Ares, J.O.; Rossi, B.E. Vegetation Heterogeneity in Monte Desert Ecosystems: A Multi-Scale Approach Linking Patterns and Processes. *J. Arid Environ.* **2009**, *73*, 182–191. [[CrossRef](#)]

32. Marquez, J.; Pastran, G.; Ortiz, G. Los Bosques de Algarrobos Del Gran Bajo Oriental Del Departamento Valle Fértil. San Juan, Argentina. *Rev. Cienc.* **1992**, *1*, 2.
33. Villagra, P.E.; Defossé, G.E.; Del Valle, H.F.; Tabeni, S.; Rostagno, M.; Cesca, E.; Abraham, E. Land Use and Disturbance Effects on the Dynamics of Natural Ecosystems of the Monte Desert: Implications for Their Management. *J. Arid Environ.* **2009**, *73*, 202–211. [\[CrossRef\]](#)
34. Ministerio de Ambiente y Desarrollo Sostenible de la Nación. *Informe Nacional Segundo Inventario Nacional de Bosques Nativos (INBN 2)*; Ministerio de Ambiente y Desarrollo Sostenible de la Nación: Buenos Aires, Argentina, 2022.
35. Dale, V.H.; Beyeler, S.C. Challenges in the Development and Use of Ecological Indicators. *Ecol. Indic.* **2001**, *1*, 3–10. [\[CrossRef\]](#)
36. Conti, G.; Gorné, L.D.; Zeballos, S.R.; Lipoma, M.L.; Gatica, G.; Kowaljew, E.; Whitworth-Hulse, J.I.; Cuchietti, A.; Poca, M.; Pestoni, S.; et al. Developing Allometric Models to Predict the Individual Aboveground Biomass of Shrubs Worldwide. *Glob. Ecol. Biogeogr.* **2019**, *28*, 961–975. [\[CrossRef\]](#)
37. Chave, J.; Réjou-Méchain, M.; Búrquez, A.; Chidumayo, E.; Colgan, M.S.; Delitti, W.B.C.; Duque, A.; Eid, T.; Fearnside, P.M.; Goodman, R.C.; et al. Improved Allometric Models to Estimate the Aboveground Biomass of Tropical Trees. *Glob. Change Biol.* **2014**, *20*, 3177–3190. [\[CrossRef\]](#)
38. Atencia, M.E. *Densidad de Maderas (kg/m³) Ordenadas por Nombre Común*; INTI/CITEMA: Buenos Aires, Argentina, 2003.
39. Gorelick, N.; Hancher, M.; Dixon, M.; Ilyushchenko, S.; Thau, D.; Moore, R. Google Earth Engine: Planetary-Scale Geospatial Analysis for Everyone. *Remote Sens. Environ.* **2017**, *202*, 18–27. [\[CrossRef\]](#)
40. Goirán, S.B.; Aranibar, J.N.; Gomez, M.L. Heterogeneous Spatial Distribution of Traditional Livestock Settlements and Their Effects on Vegetation Cover in Arid Groundwater Coupled Ecosystems in the Monte Desert (Argentina). *J. Arid Environ.* **2012**, *87*, 188–197. [\[CrossRef\]](#)
41. Campos, V.E.; Gatica, G.M.; Cappa, F.M.; Giannoni, S.M.; Campos, C.M. Remote Sensing Data to Assess Compositional and Structural Indicators in Dry Woodland. *Ecol. Indic.* **2018**, *88*, 63–70. [\[CrossRef\]](#)
42. Campos, V.E.; Fernandez Maldonado, V.N.; Amatta, E. Passive and Active Remote Sensing Data as Indicators of Vegetation Condition in Dry Woodland. *J. Indian Soc. Remote Sens.* **2022**, *50*, 815–831. [\[CrossRef\]](#)
43. Campos, V.E.; Cappa, F.M.; Gatica, G.; Campos, C.M. Drivers of Plant Species Richness and Structure in Dry Woodland of *Prosopis Flexuosa*. *Acta Oecologica* **2020**, *109*, 103654. [\[CrossRef\]](#)
44. Gao, X.; Huete, A.R.; Ni, W.; Miura, T. Optical–Biophysical Relationships of Vegetation Spectra without Background Contamination. *Remote Sens. Environ.* **2000**, *74*, 609–620. [\[CrossRef\]](#)
45. Huete, A.; Didan, K.; Miura, T.; Rodriguez, E.P.; Gao, X.; Ferreira, L.G. Overview of the Radiometric and Biophysical Performance of the MODIS Vegetation Indices. *Remote Sens. Environ.* **2002**, *83*, 195–213. [\[CrossRef\]](#)
46. Huete, A.R. A Soil-Adjusted Vegetation Index (SAVI). *Remote Sens. Environ.* **1988**, *25*, 295–309. [\[CrossRef\]](#)
47. Marsett, R.C.; Qi, J.; Heilman, P.; Biedenbender, S.H.; Carolyn Watson, M.; Amer, S.; Weltz, M.; Goodrich, D.; Marsett, R. Remote Sensing for Grassland Management in the Arid Southwest. *Rangel. Ecol. Manag.* **2006**, *59*, 530–540. [\[CrossRef\]](#)
48. Crist, E.P.; Cicone, R. Application of the Tasseled Cap Concept to Simulated Thematic Mapper Data. *Photogramm. Eng. Remote Sens.* **1984**, *50*, 343–352.
49. Kauth, R.J.; Thomas, G.S. The Tasseled Cap—A Graphic Description of the Spectral-Temporal Development of Agricultural Crops as Seen by LANDSAT. In Proceedings of the Symposium on Machine Processing of Remotely Sensed Data, West Lafayette, IN, USA, 29 June–1 July 1976; pp. 41–51.
50. Ozkan, U.Y.; Demirel, T. The Influence of Window Size on Remote Sensing-Based Prediction of Forest Structural Variables. *Ecol. Process.* **2021**, *10*, 60. [\[CrossRef\]](#)
51. Bolker, B.M.; Brooks, M.E.; Clark, C.J.; Geange, S.W.; Poulsen, J.R.; Stevens, M.H.H.; White, J.-S.S. Generalized Linear Mixed Models: A Practical Guide for Ecology and Evolution. *Trends Ecol. Evol.* **2009**, *24*, 127–135. [\[CrossRef\]](#)
52. Zuur, A.F.; Ieno, E.N.; Walker, N.J.; Saveliev, A.A.; Smith, G.M. GLM and GAM for Count Data. In *Mixed Effects Models and Extensions in Ecology with R*; Zuur, A.F., Ieno, E.N., Walker, N., Saveliev, A.A., Smith, G.M., Eds.; Springer: New York, NY, USA, 2009; pp. 209–243, ISBN 978-0-387-87458-6.
53. Burnham, K.P.; Anderson, D.R. Multimodel Inference: Understanding AIC and BIC in Model Selection. *Sociol. Methods Res.* **2004**, *33*, 261–304. [\[CrossRef\]](#)
54. Moritz, S.; Bartz-Beielstein, T. imputeTS: Time Series Missing Value Imputation in R. *R J.* **2017**, *9*, 207. [\[CrossRef\]](#)
55. Abatzoglou, J.T.; Dobrowski, S.Z.; Parks, S.A.; Hegewisch, K.C. TerraClimate, a High-Resolution Global Dataset of Monthly Climate and Climatic Water Balance from 1958–2015. *Sci. Data* **2018**, *5*, 170191. [\[CrossRef\]](#)
56. Wickham, H. *Tidyverse: Easily Install and Load the “Tidyverse”*, R Package Version 2.0.0; R Foundation for Statistical Computing: Vienna, Austria, 2016.
57. Wei, T.; Simko, V. *Corrplot: Visualization of a Correlation Matrix*, R Package Version 0.95; R Foundation for Statistical Computing: Vienna, Austria, 2010.

58. Bates, D.; Maechler, M.; Bolker, B.; Walker, S. *lme4: Linear Mixed-Effects Models Using “Eigen” and S4*, R Package Version 1.1-38; R Foundation for Statistical Computing: Vienna, Austria, 2003.
59. Bartoń, K. *MuMIn: Multi-Model Inference*, R Package Version 1.48.11; R Foundation for Statistical Computing: Vienna, Austria, 2010.
60. Ripley, B.; Venables, B. *MASS: Support Functions and Datasets for Venables and Ripley’s MASS*, R Package Version 7.3-65; R Foundation for Statistical Computing: Vienna, Austria, 2009.
61. Lesnoff, M.; Lancelot, R. *Aod: Analysis of Overdispersed Data*, R Package Version 1.3.3; R Foundation for Statistical Computing: Vienna, Austria, 2005.
62. Burrell, A. *TSS.RESTREND: Time Series Segmentation of Residual Trends*, R Package Version 0.3.1; R Foundation for Statistical Computing: Vienna, Austria, 2016.
63. Cohen, W.B.; Spies, T.A.; Fiorella, M. Estimating the Age and Structure of Forests in a Multi-Ownership Landscape of Western Oregon, U.S.A. *Int. J. Remote Sens.* **1995**, *16*, 721–746. [\[CrossRef\]](#)
64. Cohen, W.B.; Spies, T.A. Estimating Structural Attributes of Douglas-Fir/Western Hemlock Forest Stands from Landsat and SPOT Imagery. *Remote Sens. Environ.* **1992**, *41*, 1–17. [\[CrossRef\]](#)
65. Gizachew, B.; Solberg, S.; Næsset, E.; Gobakken, T.; Bollandsås, O.M.; Breidenbach, J.; Zahabu, E.; Mauya, E.W. Mapping and Estimating the Total Living Biomass and Carbon in Low-Biomass Woodlands Using Landsat 8 CDR Data. *Carbon Balance Manag.* **2016**, *11*, 13. [\[CrossRef\]](#) [\[PubMed\]](#)
66. Powell, S.L.; Cohen, W.B.; Healey, S.P.; Kennedy, R.E.; Moisen, G.G.; Pierce, K.B.; Ohmann, J.L. Quantification of Live Aboveground Forest Biomass Dynamics with Landsat Time-Series and Field Inventory Data: A Comparison of Empirical Modeling Approaches. *Remote Sens. Environ.* **2010**, *114*, 1053–1068. [\[CrossRef\]](#)
67. Fassnacht, F.E.; Hartig, F.; Latifi, H.; Berger, C.; Hernández, J.; Corvalán, P.; Koch, B. Importance of Sample Size, Data Type and Prediction Method for Remote Sensing-Based Estimations of Aboveground Forest Biomass. *Remote Sens. Environ.* **2014**, *154*, 102–114. [\[CrossRef\]](#)
68. Liu, Z.; Wimberly, M.C.; Dwomoh, F.K. Vegetation Dynamics in the Upper Guinean Forest Region of West Africa from 2001 to 2015. *Remote Sens.* **2017**, *9*, 5. [\[CrossRef\]](#)
69. Gasparri, N.I.; Parmuchi, M.G.; Bono, J.; Karszenbaum, H.; Montenegro, C.L. Assessing Multi-Temporal Landsat 7 ETM+ Images for Estimating above-Ground Biomass in Subtropical Dry Forests of Argentina. *J. Arid Environ.* **2010**, *74*, 1262–1270. [\[CrossRef\]](#)
70. Luz, L.R.; Giongo, V.; Santos, A.M.D.; Lopes, R.J.D.C.; Júnior, C.D.L. Biomass and Vegetation Index by Remote Sensing in Different Caatinga Forest Areas. *Ciênc. Rural* **2022**, *52*, e20201104. [\[CrossRef\]](#)
71. Khan, M.N.; Tan, Y.; Gul, A.A.; Abbas, S.; Wang, J. Forest Aboveground Biomass Estimation and Inventory: Evaluating Remote Sensing-Based Approaches. *Forests* **2024**, *15*, 1055. [\[CrossRef\]](#)
72. Cappa, F.; Campos, V.E.; Barri, F.R.; Ramos, L.; Campos, C.M. Environmental and Biological Factors Affecting the Abundance of *Prosopis flexuosa* Saplings in the Central-West Monte of Argentina. *For. Ecosyst.* **2022**, *9*, 100010. [\[CrossRef\]](#)
73. Valtonen, A.; Korkiatupa, E.; Holm, S.; Malinga, G.M.; Nakadai, R. Remotely Sensed Vegetation Greening along a Restoration Gradient of a Tropical Forest, Kibale National Park, Uganda. *Land Degrad. Dev.* **2021**, *32*, 5166–5177. [\[CrossRef\]](#)
74. Contreras, S.; Jobbágy, E.G.; Villagra, P.E.; Noretto, M.D.; Puigdefábregas, J. Remote Sensing Estimates of Supplementary Water Consumption by Arid Ecosystems of Central Argentina. *J. Hydrol.* **2011**, *397*, 10–22. [\[CrossRef\]](#)
75. Chazdon, R.L. Landscape Restoration, Natural Regeneration, and the Forests of the Future. *Ann. Mo. Bot. Gard.* **2017**, *102*, 251–257. [\[CrossRef\]](#)
76. Long, Q.; Wang, F.; Ge, W.; Jiao, F.; Han, J.; Chen, H.; Roig, F.A.; Abraham, E.M.; Xie, M.; Cai, L. Temporal and Spatial Change in Vegetation and Its Interaction with Climate Change in Argentina from 1982 to 2015. *Remote Sens.* **2023**, *15*, 1926. [\[CrossRef\]](#)
77. Ribeiro, E.M.S.; Arroyo-Rodríguez, V.; Santos, B.A.; Tabarelli, M.; Leal, I.R. Chronic Anthropogenic Disturbance Drives the Biological Impoverishment of the Brazilian Caatinga Vegetation. *J. Appl. Ecol.* **2015**, *52*, 611–620. [\[CrossRef\]](#)
78. Szymański, C.; Villagra, P.E.; Aschero, V.; Alvarez, J.A. Interactive Effects of Chronic Anthropogenic Disturbances on *Prosopis* Woodland Structure in the Central Monte, Argentina. *Ecol. Aust.* **2022**, *32*, 108–121. [\[CrossRef\]](#)
79. Kéfi, S.; Génin, A.; Garcia-Mayor, A.; Guirado, E.; Cabral, J.S.; Berdugo, M.; Guerber, J.; Solé, R.; Maestre, F.T. Self-Organization as a Mechanism of Resilience in Dryland Ecosystems. *Proc. Natl. Acad. Sci. USA* **2024**, *121*, e2305153121. [\[CrossRef\]](#)
80. Giordano, C.V.; Guevara, A.; Boccalandro, H.E.; Sartor, C.; Villagra, P.E. Water Status, Drought Responses, and Growth of *Prosopis flexuosa* Trees with Different Access to the Water Table in a Warm South American Desert. *Plant Ecol.* **2011**, *212*, 1123–1134. [\[CrossRef\]](#)
81. Jobbágy, E.G.; Noretto, M.D.; Villagra, P.E.; Jackson, R.B. Water Subsidies from Mountains to Deserts: Their Role in Sustaining Groundwater-Fed Oases in a Sandy Landscape. *Ecol. Appl.* **2011**, *21*, 678–694. [\[CrossRef\]](#) [\[PubMed\]](#)
82. Ambite, S.; Ferrero, M.E.; Piraino, S.; Badagian, J.; Muñoz, A.A.; Aguilera-Betti, I.; Gamazo, P.; Roig, F.A.; Lucas, C.; Prosopis, L. Woody Growth in Relation to Hydrology in South America: A Review. *Dendrochronologia* **2022**, *76*, 126017. [\[CrossRef\]](#)

83. He, P.; Ma, J.; Ye, H.; Han, Z.; Ma, X.; Alitengbieke, H.; Shi, M.; Liu, H.; Wang, H.; Sun, Z. Satellite Greenness and Solar-Induced Chlorophyll Fluorescence Reveal Reverse Desertification in Gurbantunggut Desert. *Ecol. Appl.* **2023**, *33*, e2757. [[CrossRef](#)] [[PubMed](#)]
84. Venter, Z.S.; Scott, S.L.; Desmet, P.G.; Hoffman, M.T. Application of Landsat-Derived Vegetation Trends over South Africa: Potential for Monitoring Land Degradation and Restoration. *Ecol. Indic.* **2020**, *113*, 106206. [[CrossRef](#)]
85. Liang, S.; Ziegler, A.D.; Li, L.Z.X.; Wu, J.; Wang, D.; Zeng, Z. Interplay of Greening and ENSO on Biosphere–Atmosphere Processes in Australia. *Geosci. Lett.* **2022**, *9*, 43. [[CrossRef](#)]
86. Benedictto, M.N.; Gómez-Valencia, B.; Torrella, S.A. Structural and Functional Characterization of the Dry Forest in Central Argentine Chaco. *Madera Bosques* **2019**, *25*, 2. [[CrossRef](#)]
87. Ogle, K.; Reynolds, J.F. Plant Responses to Precipitation in Desert Ecosystems: Integrating Functional Types, Pulses, Thresholds, and Delays. *Oecologia* **2004**, *141*, 282–294. [[CrossRef](#)]
88. Lovino, M.A.; Müller, G.V.; Pierrestegui, M.J.; Espinosa, E.; Rodríguez, L. Extreme Precipitation Events in the Austral Chaco Region of Argentina. *Int. J. Climatol.* **2022**, *42*, 5985–6006. [[CrossRef](#)]
89. Minetti, J.L.; Vargas, W.M.; Poblete, A.G.; de la Zerda, L.R.; Acuña, L.R. Regional Droughts in Southern South America. *Theor. Appl. Climatol.* **2010**, *102*, 403–415. [[CrossRef](#)]
90. Barchuk, A.H.; del Pilar Díaz, M. Regeneration and Structure of *Aspidosperma Quebracho-Blanco* Schl. in the Arid Chaco (Córdoba, Argentina). *For. Ecol. Manag.* **1999**, *118*, 31–36. [[CrossRef](#)]
91. Keeley, J.E. Recruitment of Seedlings and Vegetative Sprouts in Unburned Chaparral. *Ecology* **1992**, *73*, 1194–1208. [[CrossRef](#)]
92. Burrell, A.L.; Evans, J.P.; De Kauwe, M.G. Anthropogenic Climate Change Has Driven over 5 Million Km² of Drylands towards Desertification. *Nat. Commun.* **2020**, *11*, 3853. [[CrossRef](#)]
93. Burrell, A.L.; Evans, J.P.; Liu, Y. The Addition of Temperature to the TSS-RESTREND Methodology Significantly Improves the Detection of Dryland Degradation. *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.* **2019**, *12*, 2342–2348. [[CrossRef](#)]
94. Gedefaw, M.; Geli, H.; Abera, T.; Yadav, K. Drought as a Trigger of Rangeland Degradation and Land Cover Changes in Dryland Ecosystems in New Mexico, USA. In Proceedings of the AGU Fall Meeting 2021, New Orleans, LA, USA, 13–17 December 2021; p. H51H-03.
95. Liu, Z.; Lin, H.; Li, H.; Li, M.; Zhou, P.; Wang, Z.; Niu, J. Response Mechanisms of Vegetation Productivity to Water Variability in Arid and Semi-Arid Areas of China: A Decoupling Analysis of Soil Moisture and Precipitation. *Atmosphere* **2025**, *16*, 933. [[CrossRef](#)]
96. Fang, Q.; Zhao, L.; Liao, G.; Wang, Y.; Meng, C.; Hu, X.; Wang, F.; Wang, Y. Decoupling Climate and Vegetation Impacts on Hydrological Processes in Semi-Arid Regions Using an Improved Grid-Scale Budyko Model. *J. Hydrol. Reg. Stud.* **2025**, *61*, 102691. [[CrossRef](#)]
97. Figueroa, A.; Soler, R.; Campos, V. Human-Driven Land-Use Change on Native Forests in Argentina: A Literature Review of Ecological Attributes and Regional Patterns. *Int. For. Rev.* **2025**, *27*, 337–374. [[CrossRef](#)]
98. Costa, G.B.; Mendes, K.R.; Viana, L.B.; Almeida, G.V.; Mutti, P.R.; e Silva, C.M.S.; Bezerra, B.G.; Marques, T.V.; Ferreira, R.R.; Oliveira, C.P.; et al. Seasonal Ecosystem Productivity in a Seasonally Dry Tropical Forest (Caatinga) Using Flux Tower Measurements and Remote Sensing Data. *Remote Sens.* **2022**, *14*, 3955. [[CrossRef](#)]
99. Campos, V.E.; Figueroa-Masanet, A. A Systematic Review of Remote Sensing Data to Assess Dry Forests Attributes. *Bosque* **2024**, *45*, 17–41. [[CrossRef](#)]
100. Di Leo, N.; Barbona, I.; Beltrán, C.; Forgioni, F.P.; Coronel, A.; Jozami, E. Temporal Variability of Spatial Patterns of Correlations between Summer Rainfall and the Oceanic Niño Index in the Pampean Region. *Sci. Total Environ.* **2024**, *955*, 176849. [[CrossRef](#)] [[PubMed](#)]
101. Di Stefano, S.; Karl, J.W.; Duniway, M.C. Using the TSS-RESTREND Methodology to Diagnose Post-Reclamation Vegetation Trends on the Western Slope of Colorado. *Reclam. Sci.* **2024**, *1*, 48–62. [[CrossRef](#)]

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