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Remote sensing depicts riparian vegetation responses to water stress in a humid Atlantic region

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Abstract

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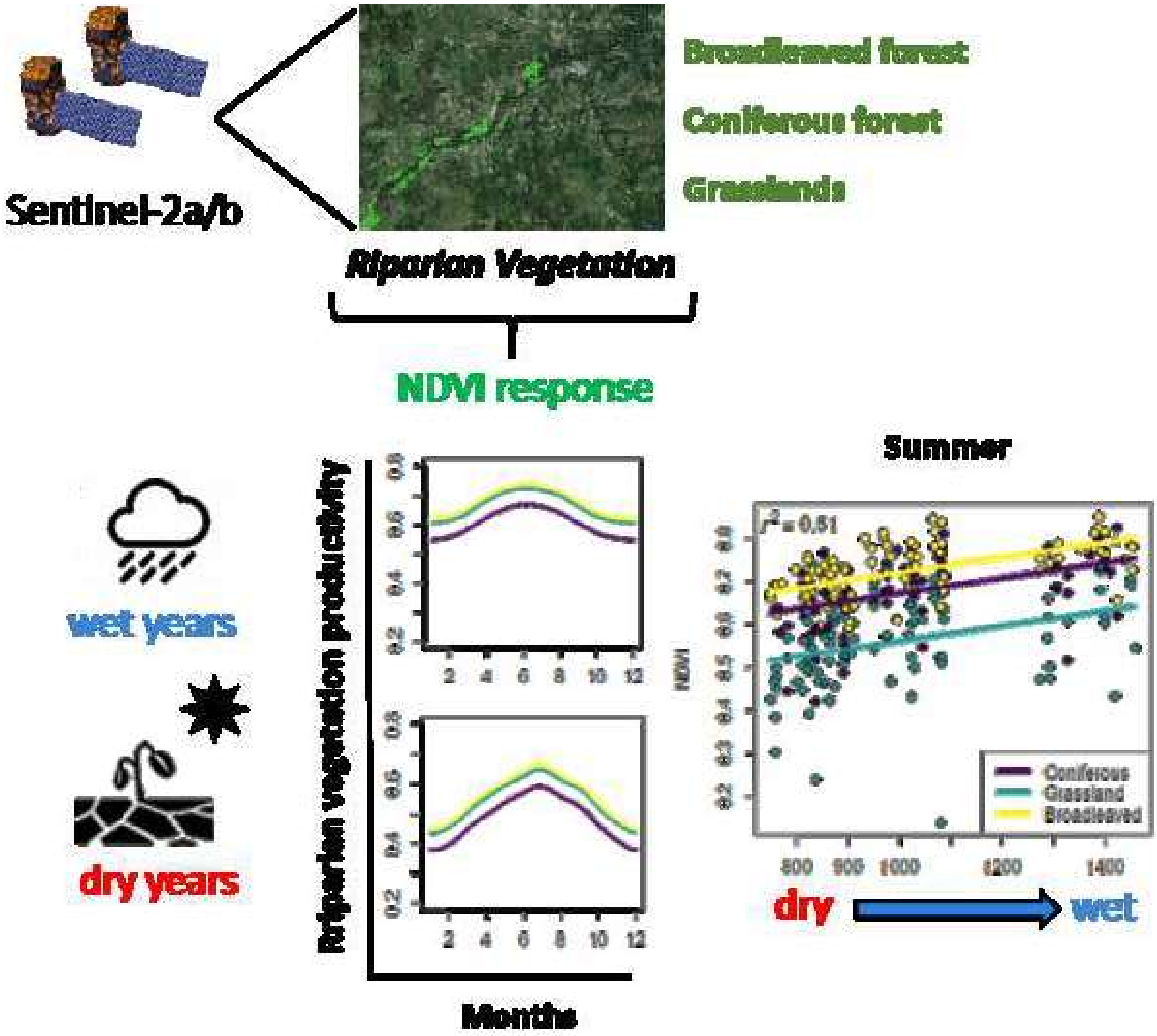
Graphical Abstract



Remote sensing depicts riparian vegetation responses to water stress in a humid Atlantic region

Highlights

- We explored intra-annual trends of riparian plants from Sentinel 2 images
- Reduced annual rainfall induced detectable intra-annual changes in plant productivity
- Temperature and elevation had a lower influence on plant productivity
- Vegetation types responded similarly to water stress but had different basal levels

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Keywords: NDVI, primary productivity, forestry, Sentinel 2, climate change, rivers

1. Introduction

Riparian zones represent transitional areas occurring between land and freshwater ecosystems, that provide many ecosystem functions and services related to water quality, microclimate regulation, structural habitat for wildlife, energy base for the food web, and bank stability (Naiman *et al*., 2005). Particularly, riparian plants represent a primary energy source for in-stream consumers, especially in headwater sections, having a strong influence on the structure of freshwater communities (e.g. macroinvertebrate; Ono *et al*., 2020). Moreover, the composition and structure of riparian vegetation can affect the suitability of habitat for riparian predators as well as the terrestrial stages of aquatic organisms (Larsen *et al*., 2015). Riparian vegetation provides shade and regulates microclimate conditions, which can influence the activity and dispersal patterns of several adult aquatic insects (e.g. Ephemeroptera, Plecoptera and Trichoptera) and amphibians (Collier and Smith, 2000; Briers *et al*., 2003; Kominoski *et al.*, 2012). In addition, riparian vegetation can capture and filter surface runoff due to physical impact of living and dead plants on hydraulics, mitigating impacts of sedimentation or nutrients on aquatic ecosystems (Dosskey *et al.*, 2010). However, riparian ecosystems are exposed to multiple anthropogenic pressures, such as agriculture, climate change or hydromorphological alterations, which deteriorate their health (Bruno *et al.*, 2016; Stella and Bendix, 2019).

Climate change is expected to cause shifts in precipitation and stream runoff patterns, including extreme differences between high and low streamflow, reduce groundwater recharge, alter nutrient dynamics and ecosystem functions (Johnson *et al*., 2012; Raymondi *et al.*, 2013). Drought is one of the most dramatic consequences of climate change with impacts on the biosphere. Although drought events are common in arid or semi-arid and Mediterranean climate regions, with documented impacts on freshwater ecosystems (e.g. Bunn *et al.*, 2006), these events are intensifying across the globe even in humid and temperate regions (Gómez-Gener *et al*., 2020; Masante *et al*., 2018). This may be the case of northwest Portugal, located in a transition between Mediterranean and Atlantic climate, where mean annual rainfall can be greater than 2500 mm (Trigo and Da Camara, 2000). Indeed, in this region, a strong reduction in mean precipitation and duration of the rainy season is expected to occur according to climate change scenarios (IPCC 2014; Miranda *et al*., 2002; Nunes *et al*., 2019).

These changes in climate may lead to significant alterations in several physiological aspects and phenophases of riparian plants, such as, leaf unfolding and flowering of plants in spring or colour changing and leaf fall in autumn (Gordo and Sanz, 2010). The effects of changing climate have been also associated with a considerable increase in the susceptibility of riparian plant species to pathogens and insect pests, leading to regional tree die-offs

(Breshears *et al.*, 2005) and changes in the distribution of vegetation (Bodner and Robles, 2017). Moreover, physiological performance of plant responses to climate stress may vary between different plant species and tissues (Garssen *et al.*, 2014; Sun *et al.,* 2020). For example, willows (Salix sp.) are considered more sensitive to drought than cottonwoods (Populus sp.), due to their smaller seed size and a slower growth of roots (Amlin and Rood 2002). In addition, gradual climate change may lead to long-term destabilisation of grassland and forest communities, favoring forest species with slower phanerophyte dynamics (Barros et al., 2018).

Since some changes may occur gradually and others may occur episodically (e.g., wildfire), long-term monitoring is needed to detect accurately where, when, and how climate effects occur for riparian vegetation (Dwire *et al.*, 2018). However, due to the spatial arrangement, dynamism and inaccessibility of riparian ecosystems, collecting data in field studies can be difficult and labour-intensive, especially for large areas (i.e. at the river basin scale or for more than 100 km of a river) (Johansen *et al.*, 2007).

Remote sensing techniques have been recognized as a convenient way to obtain continuous data, over a variety of scales and resolutions, and have been recently used for studying fluvial environments, especially the riparian zones (Tomsett and Leyland, 2019). These techniques allow a better characterization of riparian vegetation properties (e.g., diversity, biomass, health) and dynamics (e.g., phenology and phenofases) than it was previously possible (Goetz, 2006). Among the available satellite programs, the polar-orbiting Landsat-8 (launched 2013), Sentinel-2A (launched 2015) and Sentinel-2B (launched 2017) sensors offer high resolution satellite images (10 m to 30 m) multi-spectral global coverage providing images of the Earth's entire surface every few days (Li and Roy, 2017; Sudmanns *et al.*, 2019). This increased frequency of image acquisition together with the advances in the ability to process data provides new opportunities for detecting rapid or gradual riparian vegetation changes. When using remote sensing, vegetation phenology is typically monitored by means of time series of spectral vegetation indices that provide a rapid and non-destructive method to estimate the fraction of photosynthetically active radiation absorbed by Earth's vegetation (Novillo *et al.*, 2019). Among the high number of vegetation indices, the Normalized Difference Vegetation Index (NDVI) has been frequently used to assess long-term trends of vegetation (Peng *et al.*, 2012), to monitor system primary productivity over time (Stöckli and Vidale, 2004) and, more recently, to investigate productivity–diversity relationship (Wang *et al.*, 2016; Rocchini *et al.*, 2018; Torresani *et al.*, 2019). In addition, NDVI anomaly has been correlated to pant growth reduction, loss of green coverage and eventual tree mortality in response to environmental change (Camarero *et al.*, 2015; Lloret *et al.,* 2016; Breshears *et al.*, 2005; Rajah *et al.,* 2019; Gouveia *et al.*, 2017).

In this study, we applied a transferable remote sensing approach aiming to i) detect seasonal and/or intra-annual changes in riparian vegetation productivity at the river basin scale related to water stress, ii) assess how climatic variability (rainfall) and catchment attributes (elevation, vegetation type and management) influence the riparian vegetation productivity during the dry season. We employed temporal analysis (from 2015 to 2019) based on the long- term Normalized Difference Vegetation Index (NDVI) data sets derived from Sentinel-2 sensors in order to detect changes in the long- term vegetation productivity of riparian zones. We expect that decreased precipitation will increase water stress and induce loss of NDVI-based primary productivity on riparian plants. Specifically, we hypothesize that: (i) Increasing water stress inhibit plant growth and photosynthesis influencing the duration of vegetation greenness across seasons, with detectable intra-annual changes in NDVI; (ii) productivity of riparian zone during the dry season increases when more precipitation is accumulated over long periods of time, i.e. the higher the precipitation along the year, the higher the water storage and the NDVI; and (iii) water stress responses differ among riparian tree forest with higher stability of forests than grasslands due to the slower phanerophyte dynamics (they grow slower, live longer and mature later).

2. Methods

2.1 Description of study area

All study sites are at the Cávado River basin in the north Portugal (Figure 1). This basin occupies an area of 1589 km2, with a mean elevation of 564 m with several peaks of 1500m, and an average population density of ca. 200 inhabitants/km2 (minimum of 22 at Montalegre and maximum of 1770 at Braga) (Vieira *et al*., 1998). The annual average precipitation is 2348 mm, 42% of which is concentrated in the months of December, January and February. Mean annual air temperatures is 12.7°C, with a maximum average temperatures of 16.2°C and a minimum average of 8.3°C (Portal do Clima http://portaldoclima.pt/en/, Trigo and Da Camara, 2000). The water is intensively used for hydropower generation, domestic and industrial water supply and agricultural irrigation. Main tributaries are the Rabagão River (left side, with a drainage area of 257 Km2) and the Homem River (right side, with a drainage area of 246 km2).

2.2 Description of data used in the study

2.2.1 Riparian vegetation study plots

The distribution of stream riparian zones was derived from VHR Land Cover/Land Use (RZ LC/LU), a reference layer distributed by Copernicus Land Monitoring Services (https://land.copernicus.eu/local). We focused our analysis on three types of riparian vegetation: Coniferous forest, Grasslands and Broadleaved forest.

Then, twenty plots (100 x 100m) were placed within each riparian vegetation classes selecting only riparian zones without close proximity to strong human impacted areas (Rocchini *et al.*, 2016; Rocchini *et al.*, 2018; Torresani *et al.*, 2019). Successively, based on MAES concept (Mapping & Assessment of Ecosystems and their Services) and using the Level 2 and 3 of Hierarchical Nomenclature associated with the Riparian Zone layer, information on *management type* were derived characterizing each plot into natural/semi-natural or cultivated/managed areas. Specifically, in natural areas, the vegetative cover is in balance with the abiotic and biotic forces of its biotope; in semi-natural areas, vegetation is defined as not planted by humans but influenced by human actions (e.g., grazing); whereas in cultivated and managed areas, vegetation is considered artificial and requires human activities to maintain it in the long term (Di Gregorio, 2005)

Digital Surface Models (DSM's) were also used, in Quantum GIS (QGIS Development Team, 2009), to derive altitude values for each plot. To assess if river longitudinal zonation influence NDVI-based primary productivity, study plots were grouped into three river sections (upper, middle and lower), taking into account their spatial proximity.

2.2.2 Sentinel 2 imagery and NDVI

We looked for Sentinel-2 images (S2A MSI L1C) that were cloud-free in the study area (T29TNG tile) from 2015 to 2019. This resulted in 43 valid observations (date of Sentinel-2 images used are reported in Table S1) acquired from the EarthExplorer (EE) user interface (https://earthexplorer.usgs.gov/) developed by United States Geological Survey (USGS).

All images were processed for atmospheric correction, using Dark Object Substract 1 (DOS1) correction carried out with the Semi-Automatic Classification plugin (Congedo, 2016) in QGis software. Following this correction, NDVI was calculated for all 43 images as per Eq. 1 using bands 4 and 8 in Sentinel-2 which have been calibrated to sense radiation in the visible (Red) and near-infrared (NIR) regions of the spectrum respectively.

$$NDVI = (NIR - Red) / (NIR + Red) \quad \text{(Eq. 1)}$$

NDVI values range between -1.0 and 1.0 with values nearing zero and below indicating features which are not vegetated such as water, snow, ice, clouds and barren surfaces. Next, using the derived NDVI rasters (at 10m pixel size), for each plot we extracted the average NDVI values within the plot area (100 × 100 m in our case) representing our NDVI value in respect to the local riparian vegetation class.

2.2.3 *Climatic data*

Since there are few long-term weather stations within our study area, we used gridded 5km temperature and precipitation dataset (2015–2019) implemented within the CLIMALERT project (www.climalert.eu). The underlying station data set is the global surface summary of day (GSOD v7, https://www.ncei.noaa.gov/data/global-summary-of-the-day). Spatial fields have been generated using external drift kriging with elevation as additional information.

Monthly data of the covered period were extracted using QGis software. In addition, for each year we calculated several cumulative rainfall metrics for different periods by summing up month input data: May-July (rain spring); February-April (rain winter); November-January (rain autumn). Annual rainfall amounts (*rain_12m)* were computed, starting from 1 month before the beginning of the dry periods (August), as determined below. This one-month lead was introduced in order to take into account the lag between photosynthetic activity variations and those of rainfall (adapted from Camberlin *et al.*, 2007).

2.3 Data analysis

Firstly, using monthly data averaged by spatial group (n=132) and General Additive Models (GAM), we modelled intra-annual changes in NDVI. GAMs included year, month and spatial group data and an interaction between month and year as predictors. Month was smoothed using a cubic spline (k=12) to capture seasonal variation. We tested the inclusion of the interaction and the appropriateness of GAM respect to a linear model with the same set of predictors using Akaike Information Criterion (AICc) for small samples. To conduct GAMs, we used the mgcv R library (Wood, 2017).

Secondly, we used linear mixed-effect models (LME) and a multi-model inference approach (Burnham and Anderson, 2002) to explore if inter-annual changes in NDVI during the dry season were explained by catchment aspects, riparian vegetation type and/or climate. We focused on August NDVI values because it is the month of maximum hydrologic stress over the hydrological year (Trigo and Da Camara, 2000).

We first built nine LME, including (as fixed factors): exclusively catchment features (altitude, riparian vegetation type and management type), exclusively climatic predictors (with different rainfall metrics), or a combination of them, including also interactions between climate and riparian vegetation type (Table 1). Interactions allow to test if climate have similar effects across riparian land-uses. Plot was included as random factor to account for multiple measures taken at the same site. To avoid collinearity, we excluded maximum temperature from climatic predictors as it was highly correlated with rainfall variables (Pearson $r > |0.70|$). Second, based on AICc, we ranked the nine alternative models according to their AICc values and retain those with a difference of AICc ≤ 2 respect to the model showing the model ranking first (Burnham and Anderson, 2002). We also derived total model explained variance

(r^2) and Akaike weights (w) for each model to inform on the explanatory capacity and the relative likelihood of each model, respectively. For each LME model, two measures of goodness-of-fit were estimated (Nakagawa and Schielzeth, 2013): marginal goodness-of-fit (r2m) indicates the variance explained only by the fixed factors, while conditional goodness-of-fit (r2c) shows the variance accounted for by both fixed and random terms. In all cases, model residuals were visually assessed to verify linear model assumptions (Zuur *et al.*, 2009).

For final GAM and LME models, we also checked the spatial autocorrelation structure of the models' residuals using Moran's Index (Moran's I) based on each site's coordinates. When the Moran's *I* values were significantly higher than I>|0.50|, we added a residual spatial autocorrelation covariate (RAC) as predictor to capture the spatial effects non-considered by the fixed factors (Crase *et al.*, 2012). This RAC term considers the correlation between the residuals at a given plot and those from its neighbouring locations. For final GAM and LME models, we found a temporal dependence in the model residual. In these cases, we added an autoregressive integrated moving average (ARIMA) term to account for the lack of temporal independence of residuals.

3. **Results**

3.1 Inter-annual and intra-annual climatic and riparian vegetation NDVI patterns

Concerning climatic patterns, 2016 was the wettest year of the series, with a total of 1400mm of rainfall, whereas the 2017 was the driest with a total of 800mm (Figure 2a). The highest average temperature was recorded during 2018, followed by 2016 and 2017 (Figure 2b). In contrast, cooler mean temperatures were found during 2015 and 2019 (Figure 2b). Inter-annual variability of NDVI values, derived from Sentinel 2, is shown in figure 2c. Overall, NDVI values were lower during the driest year (2017) compared to the other years of the analysed temporal series. Outputs from the GAMs for modeled intra-annual changes in NDVI are shown in figure 3. Year, month, spatial group and the interaction between month and year were significant predictors of NDVI dynamics (details in Table S2). When looking at intra-annual patterns, NDVI values were generally higher in the middle and lower section of the basin compared to the upper section. Intra-annual dynamics showed marked variations across years, but they all showed maximum NDVI from March to September (Figure 3); NDVI started to decrease during autumn and showed minimum values during winter. However, the studied seasonal dynamics differed inter-annually. The seasonal maximum NDVI occurred in summer 2016 (NDVI= 0.73±0.09), whereas minimum occurred in winter 2017 (NDVI= 0.40±0.14). In 2018, high values of NDVI were maintained until November and then decreased in December. A similar seasonal behaviour was found in 2016. In contrast, in 2017 NDVI started decreasing earlier in August.

3.2 *Catchment and climate influence on NDVI during the dry season*

Model ranked first included both climatic (12 month precipitation) and catchment variables (riparian vegetation types and elevation), but no interactions between them (Model 7; ΔAICc < 2; r2m=0.73; Table 2). Model ranking also suggests that 12 month precipitation is a better predictor of NDVI than seasonal precipitation. Our model ranking also shows that interactions between climatic and catchment variables had low support. Exclusively climatic models tended to explain lower amounts of NDVI variance (r2c=4 – 11%) than exclusively catchment models (r2c=39%), while those including both types of variables had the most explanatory capacity. Precipitation, either annual or seasonal, tended to have a positive influence on NDVI.

When accounting for spatial autocorrelation in the model ranking first (Table 3), 12 month precipitation and vegetation type were still significant and explained 51% of the variance (Fig. 4). In this model, annual rainfall amounts (12 month precipitation) had a significant positive relationship with NDVI, although NDVI showed different levels for each vegetation type. Broadleaved vegetation type tends to have highest NDVI, conifers were linked to higher NDVI than grasslands. However, same effect (slope) across vegetation types was detected (Table 3; Fig. 4). Altitude and management type (natural/seminatural or cultivated/managed areas) were not significantly related to NDVI. Through the end of the dry season, NDVI values were consistently highest for broadleaved forest, intermediate for coniferous and lowest for grassland (Figure 4).

4. Discussion

Our results clearly showed that NDVI-based primary productivity has observable and quantifiable seasonality as revealed by Sentinel 2 satellite remote sensing. Marked seasonal changes between spring/summer and autumn/winter were common to all years with minimum values occurring during autumn/winter, and maximum values occurring during the spring/summer season in all years. However, differences in NDVI curves were detected between the wettest (2016 and 2018) and the driest (2017) years. These patterns suggest that the decrease in water availability influences the duration of greenness that can be interpreted as a surrogate of the length of the growing season (Fu *et al.*, 2014; Badr *et al.,* 2015). Particularly, drought has generally been associated with reduced leaf longevity in deciduous species, depending on the length and severity of the drought (Leuzinger *et al.*, 2005; Estiarte and Peñuelas, 2015). Therefore, NDVI loss can be used as a practical tool to illustrate relevant ecological consequences of water stress on riparian plants, i.e., loss of photosynthetic activity, crown partial dieback, complete or partial foliage drop and reduction leaf longevity.

In our study, NDVI-based primary productivity recovered quickly after the driest year, suggesting high resilience of riparian plants to climate variability. Many riparian plants are adapted to hydrologic, geomorphic and climatic disturbances and tolerate both seasonal and annual variation in environmental conditions (Naiman and Decamps, 1997; Stromberg *et al.*, 2013; Bruno *et al.* 2016). For example, rapid root extension, reduction in leaf size, crown dieback and branch abscission are common for riparian trees and potentially reduce the stress related to seasonally-variable water content (Stella *et al.*, 2013).

In this study, we found that river longitudinal zonation influence NDVI-based primary productivity with higher NDVI values occurring in the middle and lower sections of the river basin. Such result can be explained considering two aspects: firstly, the commonly observed unimodal pattern of riparian species richness with peaks in the middle reaches of a river (Renöfält *et al.*, 2005; Catford and Jansson, 2014); secondly, the relationship between species richness and productivity (Wang *et al.*, 2016; Torresani *et al.*, 2019). In other words, plots with high riparian species richness may tend to have a higher mean NDVI and lower variation in NDVI than plots with low species richness. Unfortunately, due to the lack of field data such hypothesis needs to be confirmed in further research.

Based on our statistical models, NDVI-based primary productivity during the dry season was positively influenced by annual rainfall for all vegetation types and the response varied slightly among types (broadleaved, coniferous, and grassland). This pattern was not influenced by elevation. Our results also suggest that reductions in annual rainfall or modifications from broadleaved vegetation to conifer or grassland types severely reduced the productivity of riparian vegetation. Regional decrease in vegetation productivity (NDVI) in southern Europe was detected during the 2003 drought episode and exhibited important differences between forest types (Gobron *et al.* 2005; Lobo and Maisongrande, 2005; Lloret *et al.*, 2007). Higher anomalies were detected in herbaceous than in woody vegetation, and in deciduous than in evergreen broadleaf forests (Lobo and Maisongrande, 2005). Among coniferous forests, NDVI decreased in Mediterranean (*Pinus halepensis*) and mesic (*Pinus sylvestris*) forests, while it did not change significantly in mountain (*Pinus uncinata*) pine forests (Lloret *et al.*, 2007). According to Barros *et al*., 2018, drought impacts on structural stability showed that forests were generally more stable than grasslands due to a slower phanerophyte dynamics and because established canopies reduced drought intensity and protected communities from extreme drought effects. However, in contrast to that predicted, we found no differences between forest types and grasslands in terms of responses to the reduction in annual rainfall (Table 3), but differences in the basal NDVI levels among vegetation types (broadleaved > conifer > grassland, Figure 4). These results suggest that changes in riparian vegetation types can severely reduce the productivity of these areas. Considering that riparian zones are the main source of carbon to streams (Lamberti *et al.*, 2017; Ledesma *et al.*, 2018), lower productivity would lead to lower concentration of stream dissolved organic carbon in the catchment (Mzobe *et al.*, 2018) with potential implications to the functioning of these freshwater ecosystems (Warren *et al.*, 2016).

Our results also confirm that variables describing rainfall occurring over shorter periods or seasons had a lower influence on NDVI than accumulated annual rainfall. Moreover, NDVI was significantly correlated with precipitation accumulated during previous periods of the year. Soil water conditions are well known to be one of the foremost drivers of species composition, biomass and plant phenology (Wang *et al.*, 2019). Particularly, soil moisture levels are strongly influenced not only by precipitation accumulated during the current growing season, but also by precipitation accumulated over a relatively long period of time (Wang *et al.*, 2003). Therefore, the more precipitation is stored along the year, the higher NDVI is expected even at the end of the dry season. Indeed, our findings suggest long lags (ca. 1-year time lag) between climatic variation and productivity of riparian vegetation.

5. Conclusion

In this study, we demonstrate that Sentinel 2 derived products have the matching temporal and spatial resolution to assess and monitor riparian ecosystem response to water stress, offering an inexpensive and consistent means of simulated time series, that could be updated regularly. The emergent long lags between climatic variation (e.g., annual precipitation) and productivity of riparian vegetation can provide interesting opportunities for forecast NDVI-based primary productivity during the dry season and develop early warnings of productivity anomalies. However, the different basal levels of productivity of grasslands, conifer and broadleaved vegetation, depicted in our study, should be considered when assessing climatic impacts on riparian vegetation. Our findings can further help to distinguish those riparian areas that are likely to be more vulnerable to changes in the annual water balance from those that are more resistant under longer-term changes in climate. Although our inferences are limited to our study area, the approach described here are readily transferable to other regions and can provide a valuable resource for prioritizing management actions for riparian areas and evaluating their effectiveness to improve adaptation to climate change.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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List of Tables

Table 1. Candidate models tested with LME (alt = altitude (masl); veg_type Riparian Vegetation Classes (Coniferous, Grassland or Broadleaved); man_type = Management Type (natural/seminatural or cultivated/managed areas); rain_m = monthly rain (August); rain_aut =cumulative rainfall during autumn; rain_spn = cumulative rainfall during spring; rain_win = cumulative rainfall during winter; rain_m:veg_type = Interaction among monthly rain and veg type; rain_12m:veg_type = Interaction among year rain and veg type).

Type of model	Model	Candidate models
Exclusively Catchment (river basin attributes)	Model 1	*alt+veg_type,+man_type*
Exclusively Climatic (rainfall metrics)	Model 2	*rain_m*
	Model 3	*rain_12m*
	Model 4	*rain_aut+ rain_spn+rain_win*
Mixed (Climatic +Catchment)	Model 5	*alt+lveg_type,+man_type+ rain_m*
	Model 6	*alt+lveg_type,+man_type+rain_m+rain_m:veg_type*
	Model 7	*alt+lveg_type,+man_type+rain_12m*
	Model 8	*alt+veg_type,+man_typee+rain_m+rain_12m:lveg_type*
	Model 9	*alt+veg_type,+man_type+rain_aut+rain_spn+rain_win*

Table 2. Model rankings and R2 for the relationship among NDVI, catchments attributes and rainfall metrics, in summer (august), 2015-2019. (alt = altitude (masl); veg_type Riparian Vegetation Classes (coniferous, grassland or broadleaved); man_type = Management Type (natural/seminatural or cultivated/managed areas); rain_m = monthly rain (August); rain_aut =cumulative rainfall during autumn; rain_spn = cumulative rainfall during spring; rain_win = cumulative rainfall during winter; rain_m:veg_type = Interaction among monthly rain and veg type; rain_12m:veg_type = Interaction among year rain and veg type).

Type of model	Candidate Models	r2c	r2m	df	logLik	AIC	delta	weight
Mixed (7)	alt+veg_type,+man_type+rain_12m	0.50	0.73	8	380.00	-744.00	0.00	0.80
Mixed (8)	alt+veg_type,+man_type+rain_12m:veg_type	0.50	0.73	10	380.55	-741.10	2.90	0.19
Mixed (9)	alt+veg_type,e+Rain_aut+rain_spn+rain_win	0.49	0.72	10	377.24	-734.48	9.52	0.01
Exclusively Climatic (3)	rain_12m	0.11	0.72	4	355.11	-702.22	41.78	0.00
Exclusively Climatic (4)	rain_aut+rain_spn+rain_win	0.11	0.72	6	352.28	-692.57	51.43	0.00
Mixed (6)	alt+veg_type,+man_type+rain_m+rain_m:veg_type	0.44	0.66	10	352.85	-685.70	58.30	0.00
Mixed (5)	alt+veg_type,+man_type+rain_m	0.43	0.65	8	349.33	-682.65	61.35	0.00
Exclusively Catchment (1)	alt+veg_type,+man_type	0.39	0.60	7	333.65	-653.30	90.70	0.00
Exclusively Climatic (2)	rain_m	0.04	0.65	4	323.23	-638.47	105.53	0.00

Table 3. Significance of fixed effect terms of the best supported model

	Estimate	**Std.Error**	**df**	**t-value**	**p-value**
(Intercept)	0.56141	0.02366	239	23.73	0.000
rain_12m	0.00018	0.00002	239	10.64	**0.000**
alt	-0.00003	0.00003	54	-1.23	0.225
veg_type_typeConiferous	-0.04830	0.01896	54	-2.55	**0.014**
veg_type_typeGrassland	-0.15953	0.01964	54	-8.12	**0.000**
man_type_typenatural/seminatural areas	-0.01855	0.01594	54	-1.16	0.250
ac	0.02004	0.00775	54	2.59	**0.012**

List of Figures

Supporting information

Table S1. Scenes used of the T29TNG tile, caught by the S2A MSI L1C sensor (*= Sentinel-2A was launched on 23 June 2015).

2015*	2016	2017	2018	2019
25 July	24 January	25 January	30 January	10 January
4 August	14 March	24 February	14 February	14 February
15 November	30 Abril	16 March	21 March	11 March
	20 May	5 Abril	25 Abril	30 Abril
	22 June	14 June	15 May	30 May
	29 July	14 July	24 June	24 July
	21 August	13 August	23 August	23 August
	30 October	2 September	22 September	12 September
	16 November	22 October	22 October	22 October
	29 December	26 November	31 December	
		21 December		

Table S2. Results of the GAMM relating NDVI intra-annual dynamic. GAM included year, month and spatial group and an interaction between month and year as predictors (n=132).

	edf	df	F	p-value
year		4.00	169.33	0.00
group		2.00	42.24	0.00
s(month):year2015	1.71	2.00	11.76	0.00
s(month):year2016	3.63	8.00	4.99	0.00
s(month):year2017	5.27	9.00	12.59	0.00
s(month):year2018	4.20	8.00	6.04	0.00
s(month):year2019	5.56	8.00	10.10	0.00
R2				84.80

Figure 1

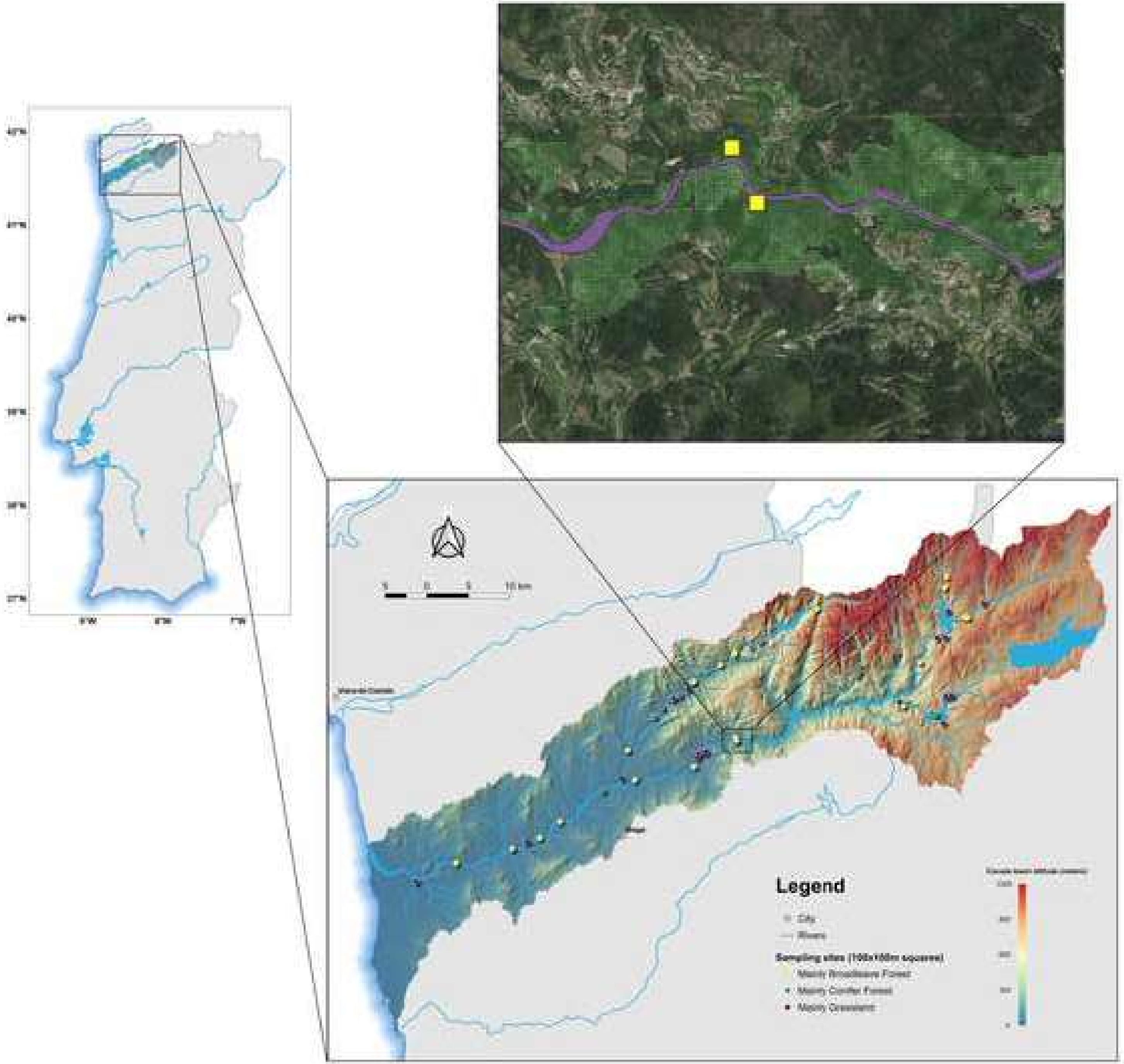

5 0 5 10 km
Legend
City
Rivers
Sampling sites (100x100m squares)
Mainly Conifer Forest
Mainly Grassland

Figure 2

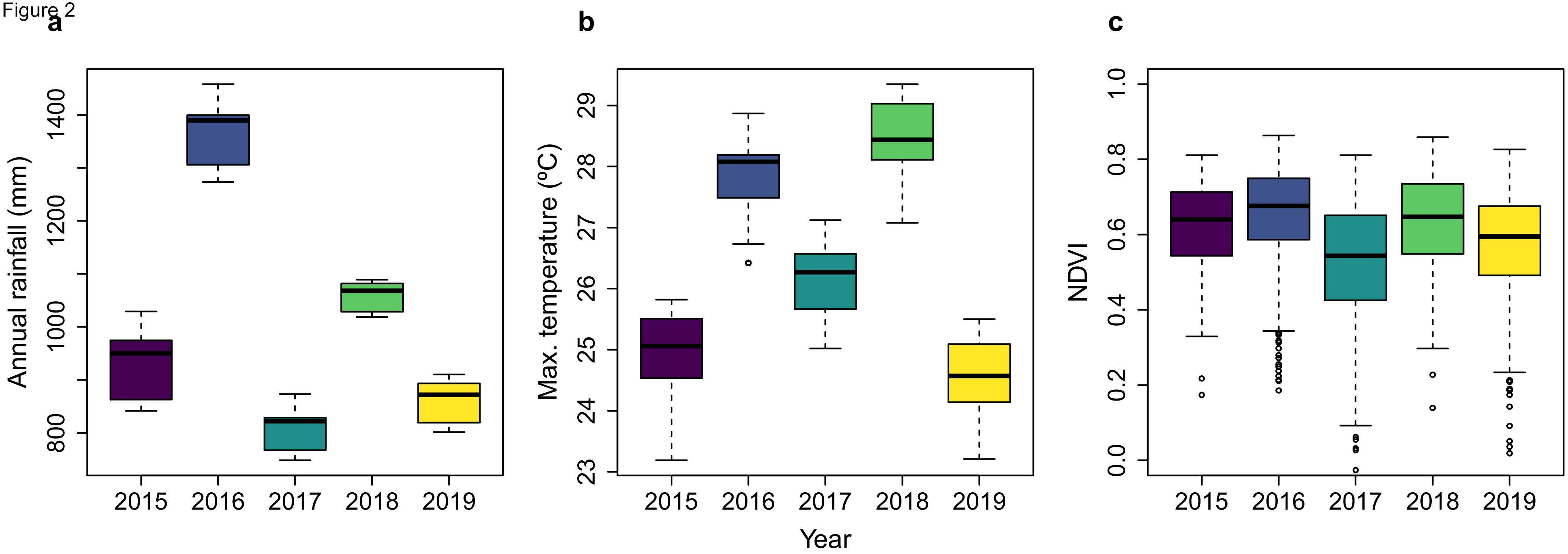

a
b
c
Annual rainfall (mm)
800
1000
1200
1400
Max. temperature (ºC)
23
24
25
26
27
28
29
NDVI
0.0
0.2
0.4
0.6
0.8
1.0
2015
2016
2017
2018
2019
Year

Figure 3

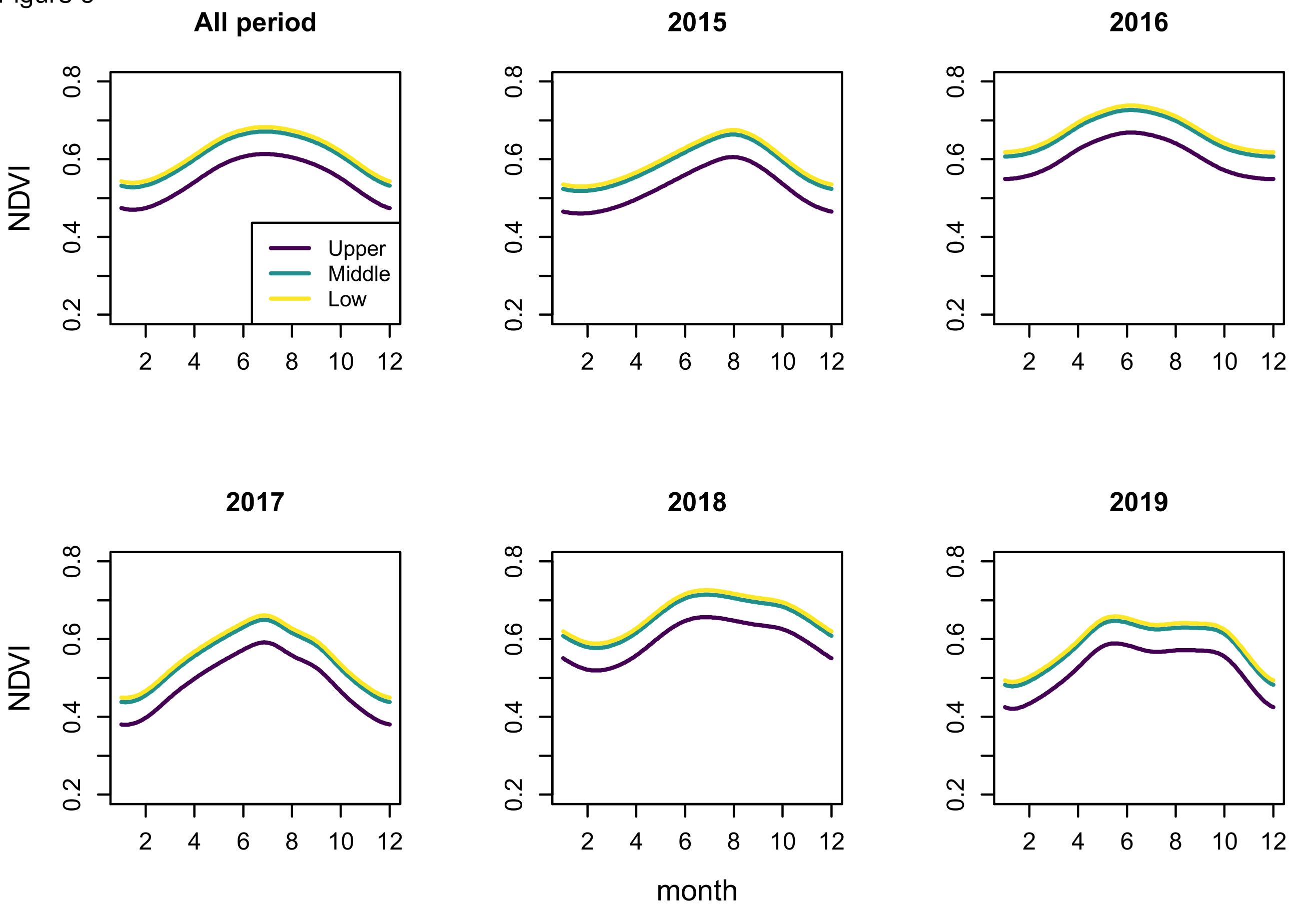
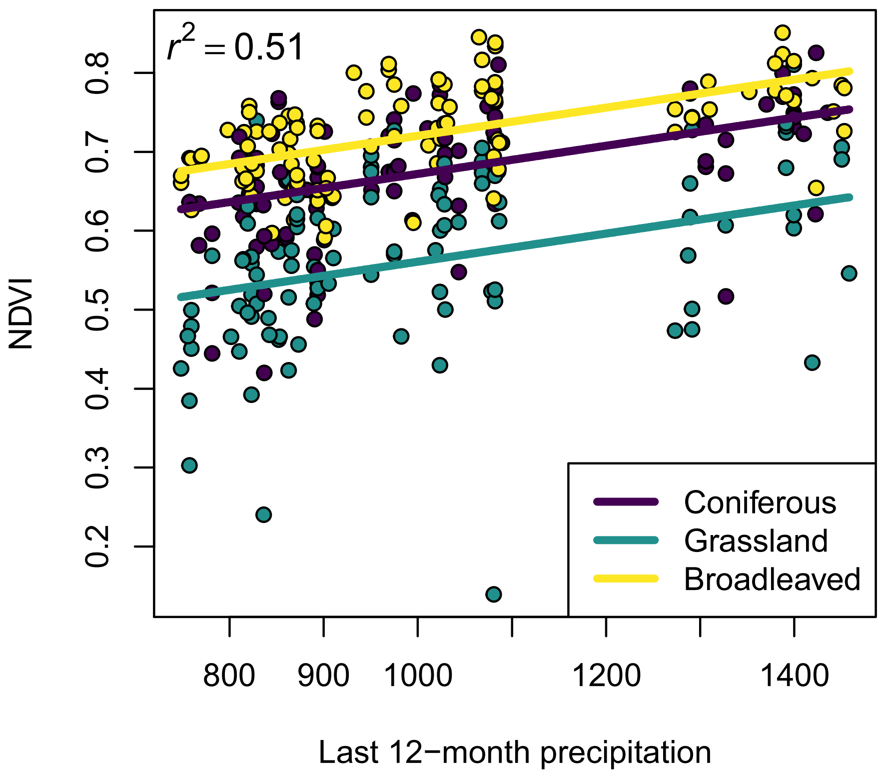

All period
2015
2016
2017
2018
2019
NDVI
NDVI
Upper
Middle
Low
0.2
0.4
0.6
0.8
2
4
6
8
10
12
month

Figure 4


$r^2 = 0.51$
NDVI
0.2
0.3
0.4
0.5
0.6
0.7
0.8
800
900
1000
1200
1400
Last 12−month precipitation
Coniferous
Grassland
Broadleaved