Regional patterns of ecosystem functional diversity in the Argentina Pampas using MODIS time-series

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Abstract

The characterization of ecosystem functioning is significant for different purposes such as biodiversity conservation and ecosystem services. A key aspect of ecosystem functioning is carbon gains, since it represents the energy available for upper trophic levels. In this sense, remote-sensing methods have allowed the study of ecosystem dynamics and spatial distribution at different spatial and temporal scales. The objectives were to describe the regional patterns of ecosystem functional diversity and to establish the importance of interannual variability in the definition of Ecosystem Functional Types (EFTs) in the Argentina Pampas. EFTs were obtained from carbon gains using a set of seven functional attributes and their interannual variations, which were retrieved from 14-year NDVI time-series. An ISODATA technique was applied to all the analyzed variables, and the clusters that best separate in the n-dimensional space were selected using discriminant analysis. The Argentina Pampas shows a high heterogeneity in the spatial patterns of ecosystem functional attributes. The annual integral of NDVI (i-NDVI, a linear estimator of net primary productivity), a complex of ecosystem functional attributes that describe the interannual variability, and the annual relative range of NDVI (RREL, ecosystem seasonality) had the highest relevance to distinguish nine EFTs in the study area. This study shows a novel approach for mapping ecosystem functioning, which reveals the importance of interannual variations. This methodology includes the effects of climate variability on ecosystem dynamics, thus enhancing our understanding of ecosystem functional diversity. The results obtained represent a baseline scenario to evaluate the effects of both land use change and climate variability on ecosystem functioning from a temporal perspective.

Keywords: ecosystem functioning; NDVI; interannual variability; discriminant analysis; climate variability; land use.

1. Introduction

As a fundamental component of biodiversity, ecosystem functioning involves evolutionary and ecological process such as the exchange of matter, energy and information (Noss, 1990). Traditionally, monitoring biodiversity has been based on structural and compositional properties, i.e., species richness, diversity indices and the spatial patterns of a system. However, the analysis of ecosystem functional properties is less frequent (Alcaraz-Segura et al., 2013). Lately, the role of ecosystem functioning has gained a strong imprint in natural resource management and biodiversity conservation (Cabello et al., 2012). This could be ascribed to the increasing evidence that ecosystem degradation is promoted by intensive human control on natural resources and the awareness of the clear dependence of ecosystem services by the human population (Alcaraz-Segura et al., 2013; Ivits et al., 2013a). On the other hand, ecosystem functional attributes have two main advantages. First, a faster response to disturbances than structural variables because of structural inertia that could show a delay in the perception of changes and disturbances (Milchunas and Lauenroth, 1995). Second, the effects of global change are evident at ecosystem level and on these functional aspects (Vitousek et al., 1997). Ecosystem Functional Types (EFTs) are defined as land surface regions with similar carbon dynamics independently of vegetation structure and composition (Alcaraz-Segura et al., 2006; Paruelo et al., 2001). EFTs are conceptually related to plant functional types (PFTs), but EFTs are defined at higher level of organization than PFTs (Paruelo et al., 2001). Thus, the idea of EFTs has been built about the spatial heterogeneity on ecosystem functioning. The knowledge of this heterogeneity provides a significant baseline to evaluate the effects of environmental and anthropogenic changes. Also, the characterization of EFTs at a regional scale could be a key feature for understanding the integrity of ecosystem functional diversity and ecosystem services (Hooper et al., 2005).

Several methodologies have been developed with the aim of characterizing functional units at a regional scale. Soriano and Paruelo (1992) made a first approach to identify vegetation and environmental units –named Biozones- based on the seasonal dynamics of aerial net primary production (ANPP) derived from satellite images. This approach has been applied in several works (Alcaraz-Segura et al., 2013, 2006; Barraza et al., 2013; Ivits et al., 2013a, 2013b; Paruelo et al., 2001). The ecosystem functional diversity in the Argentina Pampas has been analyzed within a continental context, where its high functional heterogeneity is not shown (Alcaraz-Segura et al., 2013; Müller et al., 2014; Paruelo et al., 2001). The coarse spatial resolution of datasets used is probably the main cause of failure in detecting the functional heterogeneity.

A key aspect of ecosystem functioning is carbon gains, since it represents the energy available for upper trophic levels, and their change may affect the provision of ecosystem services at a landscape scale (Paruelo et al., 2016). In this sense, radiation interception is the main process controlling carbon gains (Monteith, 1981). Among the techniques employed to estimate carbon gains, remote-sensing methods have been adequate due to the fact that they allow the study of ecosystem dynamics and spatial distribution at different spatial and temporal scales (Horning et al., 2010). Several spectral indices from remote sensors are associated to ecosystems functional attributes, such as evapotranspiration and net primary productivity (NPP) (Di Bella et al., 2000; Paruelo et al., 1997). The Normalized Difference Vegetation Index (NDVI) is one of the most commonly used indices because it is a linear estimator of the fraction of photosynthetically active radiation intercepted by vegetation (fAPAR) (Wang et al., 2004) and, hence, NDVI has been used as a proxy to describe local and regional patterns of NPP and carbon gains (Paruelo et al., 2001, 1997; Texeira et al., 2015).The analysis of long-term time series permits revealing the dynamic processes that otherwise might remain hidden to human perception (Kuenzer et al., 2015). Particularly the use of NDVI time-series has allowed us to obtain different aspects of matter and energy exchange between the biota and the atmosphere, i.e. ecosystems functional attributes (Pettorelli et al., 2005; Appendix A). These attributes allow the qualitative and quantitative characterization of ecosystem services (e.g. water cycling, carbon sequestration) (Costanza et al., 1997; Paruelo et al., 2016).

Several studies have demonstrated the implications of climate variability on ecosystem functioning at different latitudes, from arid to humid ecosystems (Broich et al., 2014; Dhakar et al., 2013; Fabricante et al., 2009; Hou et al., 2015; Leeuwen et al., 2013; Melendez-Pastor et al., 2010; Schmidt et al., 2010; Texeira et al., 2015; Weiss et al., 2004; Yang et al., 2012; Zhu and Meng, 2015). A potential way to include the effects of climate variability is through the interannual variability of ecosystem functioning, thus enhancing our understanding and characterization of the ecosystem functional diversity. Interannual climate variability usually changes regional patterns of net primary productivity (NPP) and, hence, it changes the ecosystem functional attributes (Müller et al., 2014). Although there are different methodologies to identify

EFTs, none of them considers this interannual variability. We consider that the interannual variability of ecosystem functioning is a key feature, mainly due to its strong impact on carbon dynamics.

Disturbances are so strong and fast that it is necessary to detect possible impacts on ecosystems, and these can be analyzed by evaluating functional characteristics. Therefore, the main objective was to characterize the regional patterns of ecosystem functional diversity in the Argentina Pampas from carbon dynamics derived from a set of ecosystem functional attributes of the NDVI time-series for the period 2000-2014. Furthermore, the three specific objectives were: to describe the main spatial patterns of carbon gains using a set of seven functional attributes derived from the NDVI time-series, and their interannual variability; to determine the importance of interannual variability on ecosystem functioning, and to identify Ecosystem Functional Types (EFTs) for the Argentina Pampas based on the attributes mentioned above.

2. Material and methods

2.1. Study area

We analyzed the regional patterns of ecosystem functional diversity in the Argentina Pampas (Fig. 1). The Argentina Pampas is a wide plain, characterized by high heterogeneity of landscapes and for being one the most productive areas in the country (Lara and Gandini, 2014; Matteucci, 2012). This region supports one of the largest temperate grasslands on the globe and has undergone major changes since the sixteenth century (Matteucci, 2012; Vega et al., 2009). During the last two decades, land cover changes over this area have increased (Viglizzo et al., 2001). The largest areas are sown with soybean as summer crop and wheat as winter crop followed by oats, corn, sunflower and natural or semi-natural grassland under cattle grazing (Baldi et al., 2006; Guerschman et al., 2003; Lara and Gandini, 2014).

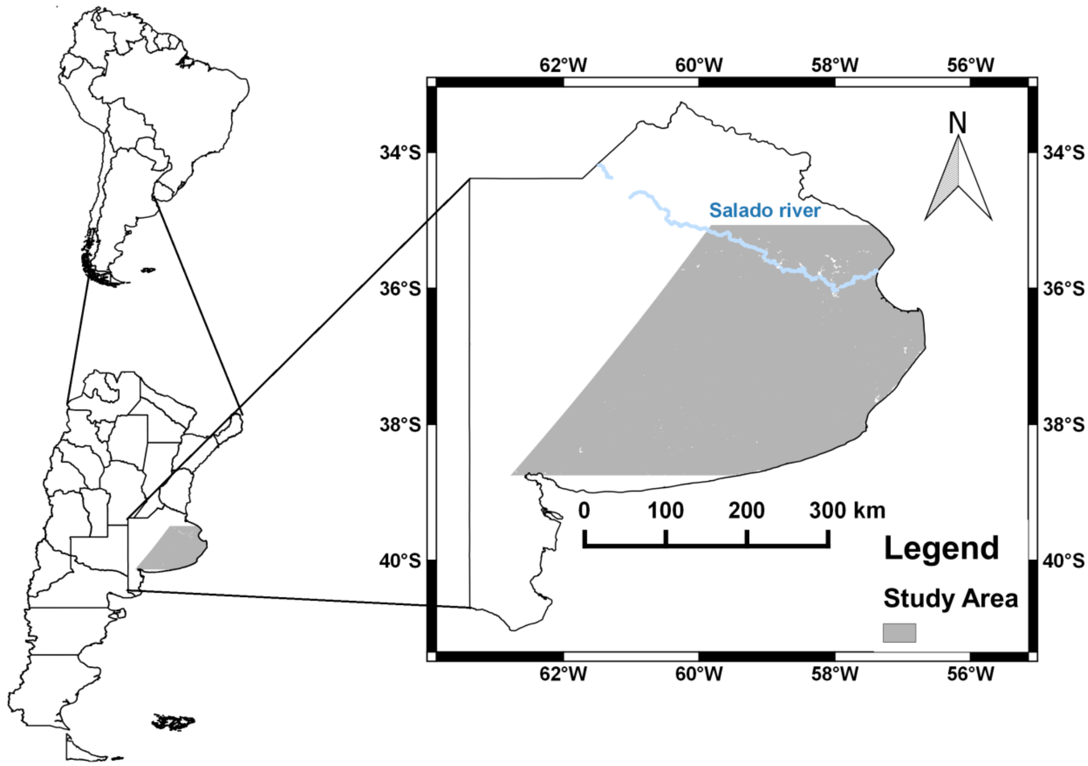

Fig. 1 Location of the study area.

2.2. *Satellite data*

We based our study on a 14-year (2000-2014) NDVI datasets obtained from satellite images. The NDVI is a spectral index calculated from the reflectance in the red (0.6 – 0.7 µm) and near-infrared wavelengths (0.7 – 1.1 µm). The contrast between red and near-infrared responses is a sensitive measure of vegetation amount, with maximum red – near-infrared differences occurring over a full canopy and minimal contrasts over targets with little or no vegetation. We used the MOD13Q1 product (version 6) from Terra's Moderate Resolution Imaging Spectroradiometer (MODIS). This dataset consists of a 16-day maximum value composite obtained by the Constrained View angle-Maximum Value Composite (CV-MVC) and Maximum Value Composite (MVC) techniques. The scenes have a spatial resolution of 250 x 250 m. The dataset used covers the period July 2000 (Julian day 177) to June 2014 (Julian day 161). This temporal window does not align with calendar years, but allowed us to have ample data of the main Southern Hemisphere growing seasons; the scene used was h13v12.

2.3. Smoothing and extraction of ecosystem functional attributes

CV-MVC and MVC techniques allow reduction of a considerable amount of noise that is present in different images (Solano et al., 2010) but do not result in noise-free products. To overcome the problems associated with remaining noise, various methods have been developed to smooth NDVI time-series. An adaptive Savitzky-Golay filter with a moving window equal to three was applied, since it shows a balanced ability to reduce noise while maintaining the NDVI time series integrity in our study area (Lara and Gandini, 2016a). Additionally, the pixel reliability band (MOD13Q1) was used to weight each pixel in the time series: value 0 (good data) had full weight (1.0), values 1-2 (marginal data, snow/ice) had half weight (0.5) and value 3 (cloudy) had low weight (0.1).

To describe the main spatial pattern of carbon gains, seven ecosystem functional attributes were extracted for each growing season for the period 2000-2014: the start of the growing season (SOS), the length of the growing season (LOS), the annual integral of NDVI (i-NDVI), the annual relative range of NDVI (RREL), the rates of increase (R-INC) and decrease (R-DEC) of the NDVI and the timing of the annual maximum NDVI (t-MAX). Both procedures (smoothing and extraction of ecosystem functional attributes) were carried out in TIMESAT program version 3.2. A brief description of these attributes and their biological significance can be found in Pettorelli et al. (2005; see Appendix A in Supplementary data). A threshold of 20% of the amplitude over the fitted time series was considered to determine the beginning and the end of the growing season.

The standard deviations (_stddev) of each functional attribute were obtained as an interannual variability indicator.

2.4. Statistical method to identify the Ecosystem Functional Types

An ISODATA technique was applied to all the analyzed variables. This technique is an unsupervised classification method that calculates class means evenly distributed in the data space and then iteratively clusters the remaining pixels using minimum distance algorithms. In each iteration means are recalculated and pixels are reclassified with respect to the new means. Frequently, the number of iterations has the major influence on the resulting clusters. Hence, ISODATA technique was executed seven times with 1, 5, 10, 25, 50, 100, and 200 iterations.

Discriminant analyses on the resulting clusters of the seven ISODATA classifications were used to select the clusters best separated in the n-dimensional space. We obtained the Wilks' lambda and the canonical correlation for each discriminant analysis. The Wilks' lambda is a standard statistic used to denote the statistical significance of the model discriminatory power, where its value will range from 0.0 (perfect discriminatory power) to 1.0 (no discriminatory power). The canonical correlation of the discriminant function indicates the proportion of total variability explained by differences between clusters. The ISODATA results with the lowest Wilks' lambda and the highest canonical correlation were selected. Finally, to facilitate the interpretation, some clusters were re-grouped by using a dendrogram analysis so that the variance within the new clusters was lower. These new clusters were considered the Ecosystem Functional Types (EFTs). We rely on the structure of correlations between ecosystem functional attributes and the fundamental discriminant functions (according to the proportion of explained variance) to interpret the meaning of each function. In order to describe the EFTs obtained in terms of their functioning, we analyzed the spatial distribution of each EFT centroid in a scatterplot of canonical scores.

2.5. Agreement between functional and structural classifications

In order to associate the EFTs with existing structural descriptions, we evaluated the percentage of agreement between the EFTs and the Ecosystem Complexes of Pampa Ecoregion defined by Matteucci (2012; Appendix B). These Ecosystem Complexes are structural units based on previous and novel phytogeographical descriptions and spatial patterns as seen on Landsat images. This evaluation only intended to be an analysis of the agreement/disagreement between structural and functional approaches of ecosystems at a regional scale.

3. Results

3.1. Spatial patterns of the ecosystem functional attributes

The mean spatial distributions of ecosystem functional attributes values are shown in Figure 2. Most of the SOS values occur between August and September (Julian days 213-263, approximately), whereas in the southwestern region SOS occurs in October-November (Julian days 274-344, approximately). In both southwestern and northeastern regions a high interannual variability for the period 2000-2014 was observed, ranging from five to six months (see Figure A1 in Supplementary data). The mean LOS values gradually increased from the southwestern to the northeastern regions of the study area (Fig. 2b). However, the interannual variability of LOS did not show a definite spatial pattern (Appendix A). The i-NDVI (linear estimator of net primary productivity) increased from the southwestern to the northeastern regions (Fig. 2c), in the same way as LOS.

The mean RREL for the period 2000-2014 showed a clear contrasting pattern with i-NDVI, i.e., areas that showed a higher productivity (i-NDVI) possessed a lower seasonality (RREL), and areas with a lower productivity showed a higher seasonality (Fig. 2d). The spatial patterns of increase (R-INC) and decrease (R-DEC) of the NDVI showed a similar pattern with the mean seasonality (Fig. 2); regions with high seasonality showed high rates of NDVI increase and decrease.

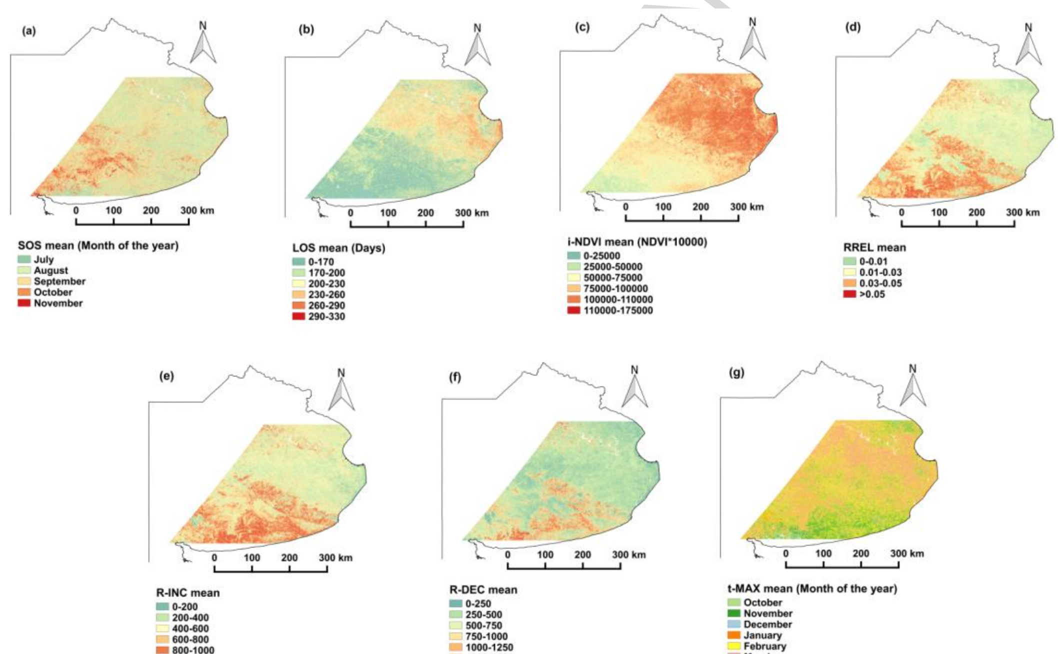

Fig. 2 Mean spatial patterns of ecosystem functional attributes for the period 2000-2014 based on NDVI time-series. (a): start of the growing season (SOS), (b): length of the growing season (LOS), (c): annual integral of NDVI (i-NDVI), (d): annual relative range of NDVI (RREL), (e): rate of increase of the NDVI (R-INC), (f): rate of decrease of the NDVI (R-DEC), (g): timing of the annual maximum NDVI (t-MAX).

The ecosystems in the Argentina Pampas differed in the timing of the annual maximum NDVI (t-MAX) (Fig. 2g). In much of the study area, the peak of NDVI (t-MAX) occurred in late summer

(February-March); whereas in the southern and northeastern pampas, the annual maximum of NDVI was observed earlier (between October-November). However, the interannual variability of t-MAX reached values between 150 and 210 days (5-6 months, approximately), especially on southwestern and northeastern regions (see Figure A1 in Supplementary data). This pattern of variability is clearly related to the SOS interannual variability.

3.2. *Regional patterns of ecosystem functional diversity*

Fifteen initial functional groups were obtained, which were grouped into nine clusters. These clusters were considered the Ecosystem Functional Types (Fig. 3). The ISODATA analyses reached major significance and discriminatory power at the 50th iteration with Wilks' lambda of 0.071 and canonical correlation of 0.858 (Table A2 in Supplementary data).

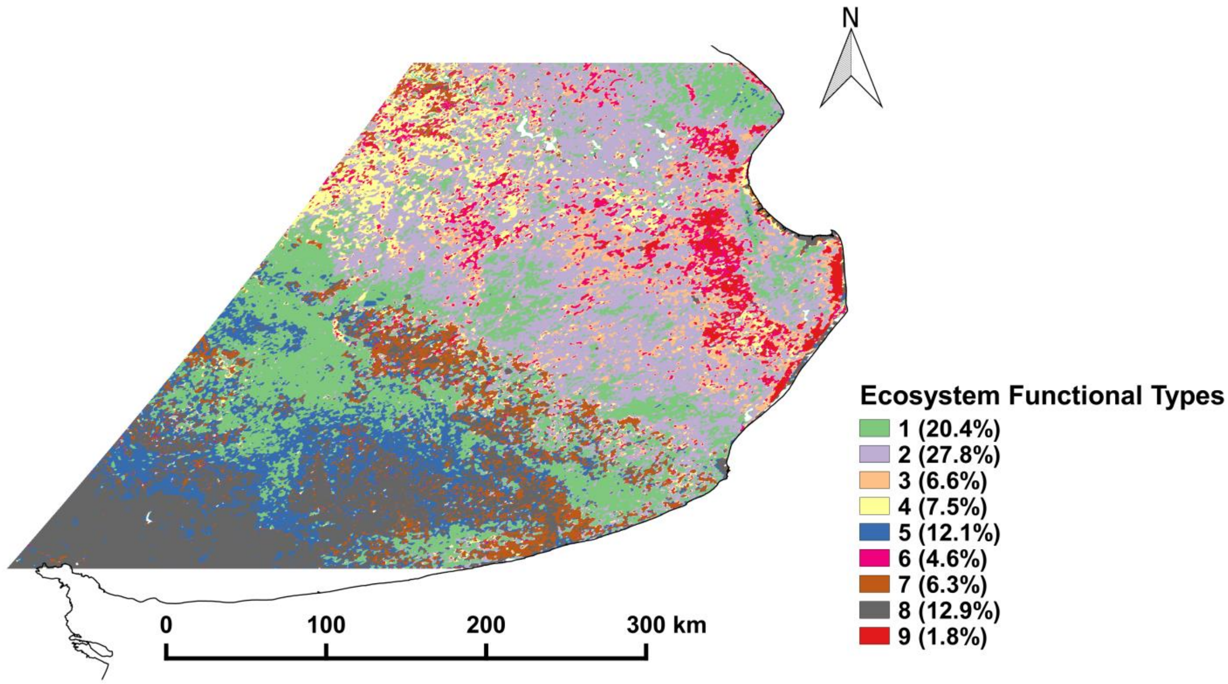

Fig. 3 Ecosystem Functional Types (EFTs) for the Argentina Pampas based on carbon dynamics derived from the NDVI dataset and its interannual variability.

The first three discriminant functions explained 95.1% of the total variation. The first function alone explained 61.5% of the variation while the second and third functions explained 24.3% and 9.3%, respectively. The first discriminant function was mostly related to the annual integral of NDVI (i-NDVI) (Table 1). The second function, which explained 24.3% of the total variation, was associated with a complex of ecosystem functional attributes that describe the interannual variability: the variability at the start of the growing season, the length of the growing season, the annual productivity and the timing of the annual maximum NDVI. Finally, seasonality showed the highest correlation on the third discriminant function. This structure of correlations between ecosystem functional attributes and the three discriminant functions allows the identification and description of three fundamental dimensions. This enabled us to characterize and distinguish the spatial patterns of ecosystem functional diversity: the first one associated with annual productivity, the second one with interannual variability of ecosystem functioning, and the third one with ecosystem seasonality.

Table 1 Correlation coefficients between ecosystems functional attributes and discriminant functions (DF). SOS: start of the growing season; LOS: length of the growing season; i-NDVI: annual integral of NDVI; RREL: annual relative range of NDVI; t-MAX: timing of the annual maximum NDVI; R-INC: NDVI increase rate; R-DEC: NDVI decrease rate. The suffix _stddev is the standard deviation of ecosystem functional attributes (interannual variability indicator).

Ecosystem functional attributes	DF 1	DF 2	DF 3
SOS	0.16	0.11	0.13
LOS	-0.60	-0.23	0.21
i-NDVI	-0.87	-0.17	-0.003
RREL	0.48	-0.46	-0.55
t-MAX	-0.16	-0.06	0.24
R-INC	0.39	-0.15	-0.41
R-DEC	0.35	-0.29	-0.41
SOS_stddev	0.17	0.81	0.34
LOS_stddev	-0.12	0.77	0.02
i-NDVI_stddev	-0.28	0.82	-0.06
RREL_stddev	0.49	0.19	0.11
t-MAX_stddev	0.14	0.81	0.27
R-INC_stddev	0.27	0.07	-0.24
R-DEC_stddev	0.34	-0.09	-0.36

The scatterplots of each functional type centroid in the space of the pairwise combination of the discriminant functions showed their main properties (Fig. 4). EFT showing high productivity had low seasonality and low interannual variability in the study area (EFT 9; Fig. 4a and 4b). This pattern was observed in a transitional zone between Flooding Pampa and Rolling Pampa (see

Appendix B). In contrast, EFT with low productivity (i.e. regions with low photosynthetic activity) had moderate interannual variability and included both low to high seasonality zones (EFT 8; Fig. 4a and 4b). This pattern occurred in semiarid areas of southwestern Pampas and includes semi-bare soil in some coastal zones. The remaining areas of the Argentina Pampas differed along an annual productivity gradient, also showing differences in seasonality and interannual variability (Fig. 4a, b and c). Within this broad group, EFTs 3 and 6 were characterized by a high annual productivity and a moderate seasonality, but EFT 6 had less interannual variability. These EFTs were observed in the Salado river floodplain. EFTs 5 and 7 showed a similar annual productivity (low to medium), but EFT 7 was associated with less interannual variability and higher seasonality. EFTs with moderate annual productivity were the most spatially representative of the Argentina Pampas (EFTs 1, 2 and 4). Alone EFT 1 and 2 represented 48.2% of the study area. EFT 1 showed a lower productivity followed by EFTs 4 and 2; whereas EFTs 1 and 2 have the highest interannual variability, EFT 4 showed low interannual variability.

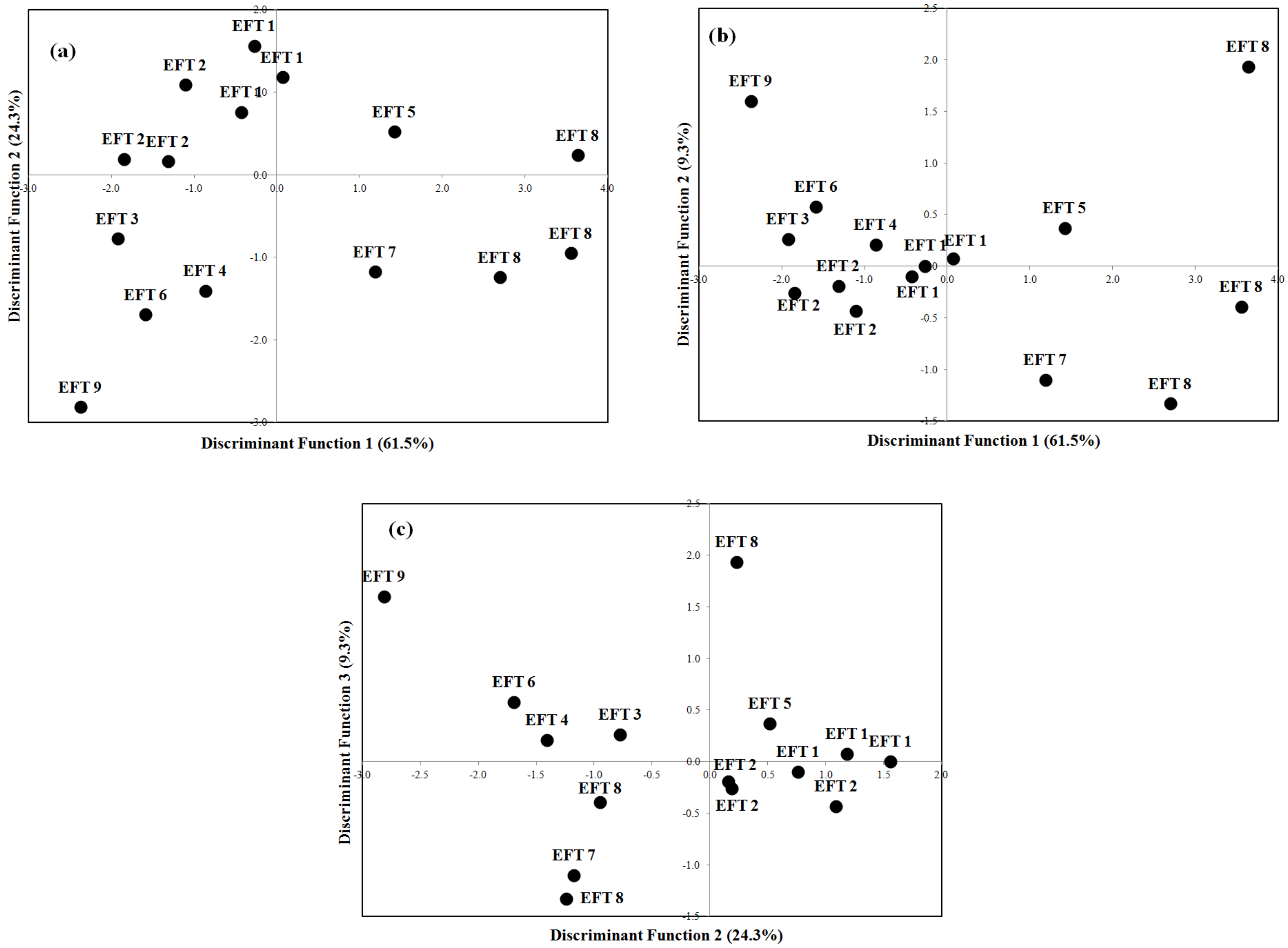

Fig. 4 Scatterplot of the Ecosystem Functional Type (EFT) centroids for the Argentina Pampas on the three discriminant functions pair wise combinations. (a) Discriminant functions 1 and 2, (b) discriminant functions 1 and 3, (c) discriminant functions 2 and 3. Repeated identifiers indicate re-grouped EFTs.

3.3. Relationship between functional and structural classifications in the Argentina Pampas

A clear association between the EFTs and Ecosystem Complexes of Pampa Ecoregion by Matteucci (2012) was not found (see Appendix B in Supplementary data). Each EFT is represented in more than one Ecosystem Complex and, at the same time, the Ecosystem Complexes include more than one EFT. Thus homogeneous structural units have high functional differences or different structural units could have similar functioning.

4. Discussion

In the Argentina Pampas, as in other productive regions of the world, the use of agricultural practices has increased, which is associated with fast crops replacement (Manuel-Navarrete et al., 2009). Thus, interannual variability represents a key variable for understanding the spatial pattern of functional diversity.

The mean spatial patterns of 14 years of ecosystem functional attributes respond, probably, to the patterns of variation of temperature, radiation and moisture or a complex combination thereof (Jolly et al., 2005; Nemani et al., 2003). According to the gradual variation of these factors, most of the functional attributes values are expected. The SOS mean patterns are more spatially heterogeneous than those found by van Leeuven et al. (2013). On the other hand, SOS interannual variability –mainly in the southwestern and northeastern regions- is higher than those found by the same authors. Possibly, the high interannual variability of SOS was associated with land cover changes influenced by climatic factors, where the rainfall appears as the main limiting factor in the region (Andrade et al., 2009; Angeles and Marini, 2014). Similar results in i-NDVI mean pattern (linear estimator of net primary productivity) were found in other works (Leeuwen et al., 2013; Paruelo et al., 2001). According to descriptions by previous research (Baldi et al., 2006; Lara and Gandini, 2014), regions with the highest annual productivity (i.e. i-NDVI values) are associated with transitional zones covered by natural or semi-natural grasslands and perennial and annual crops, whereas regions with the lowest annual productivity are dominated by double-cropping system (generally wheat-soybean crops). It should be noted that the surface of these cultivated systems has been increasing over the last 15-20 years (Vazquez and Zulaica, 2013, 2012). The spatial pattern of i-NDVI interannual variability was positively associated with LOS interannual variability, which is expected to occur regardless of vegetation type.

Ecosystems seasonality (RREL) is associated with the intra-annual variation of light interception during the growing season (Atzberger and Eilers, 2011). Thus, high seasonality indicates a noticeable intra-annual difference of photosynthetic activity (as reflected on NDVI values) that could be related to abiotic limiting factors or agricultural practices. In contrast, low seasonality indicates a great stability of photosynthetic activity, such as that of perennial vegetation. The impacts of land use on radiation interception and carbon flux seasonality are undoubted (Guerschman et al., 2003). Sown pastures tend to decrease RREL and annual crops tend to increase RREL due to their phenological characteristics. Annual crops have well-defined growing seasons (shorter than grasslands), with a period of very low or no photosynthetic activity. This produces a higher difference between maximum and minimum NDVI values than in grasslands. On the other hand, sown pastures have less cover variability throughout the growing season, which produces a similar difference between NDVI maximum and minimum values than in grasslands (Lara and Gandini, 2016b). We found a higher seasonality in the south and southwestern regions, where annual crops and double-cropping systems are dominant. A lower seasonality was observed in the central and northeastern regions that are dominated by natural and semi-natural grasslands. This spatial distribution coincides with that found by Atzberger & Eilers (2011). However, heterogeneity is higher than registered 16 years ago (Paruelo et al., 2001) when the Argentina Pampas was subjected to a strong process of agriculturization (Manuel-Navarrete et al., 2009).

Like RREL, land use management has a strong impact on t-MAX values. In the Argentina Pampas it has been demonstrated that in winter crops NDVI peak advanced by 210 days, and in summer crops the occurrence of NDVI peak was delayed by 140 days, compared to native grasslands or vegetation subjected to low-impact. A similar pattern was found in eastern Colorado (Paruelo and Lauenroth, 1995). Also in our study area, changes on spatial patterns were observed in the timing of the annual maximum NDVI between 2001(Paruelo et al., 2001) and 2014, which demonstrate the intensification of agricultural practices. Thus, ecosystem seasonality in the Argentina Pampas could be used as an indirect indicator of large land cover changes.

t-MAX interannual variability was positively related with SOS interannual variability, which indicates a strong effect of land cover types that change each season (Andrade et al., 2009; Angeles and Marini, 2014) modifying NDVI seasonal dynamics. These constant changes cause that both SOS and the t-MAX advanced or delayed their occurrence according to main land cover (winter crops, summer crops, sown pastures). This situation reveals a strong human control on seasonal carbon dynamics and on ecosystem functioning.

Ecosystem Functional Type (EFT) definitions based on ecosystem functional attributes and their interannual variability derived from remote sensing data help deepen our knowledge of the spatial and temporal patterns of ecosystem functioning at a regional scale. It could be used as appropriate background to assess the effects of environmental changes (Pettorelli et al., 2005). The characterization of EFTs is a way of identifying functional diversity at a regional (and also global) scale, associated with various processes that operate over large scales, such as the exchange of matter and energy (Noss, 1990). This identification has the advantage of detecting the effects of global change faster than other variables commonly used (Milchunas and Lauenroth, 1995; Vitousek et al., 1997). In this sense, our objective was to characterize the heterogeneity of ecosystem functioning and also to maintain the maximum explained variance between different EFTs.

Discriminant analysis allowed us to distinguish three fundamental dimensions that are capable of characterizing ecosystem functioning heterogeneity in the Argentina Pampas: i) annual productivity; ii) ecosystem functioning interannual variability and iii) ecosystem seasonality. As in other temperate regions (Alcaraz-Segura et al., 2006; Paruelo and Lauenroth, 1995) the annual integral of NDVI is the most representative indicator of the total variance of the NDVI-derived variables of annual and internannual dynamics. In this work, the annual integral of NDVI was strongly correlated with the first discriminant function that accounted for 61.5% of the total variance (Table 1).

The importance of annual productivity and ecosystem seasonality to represent the ecosystem functional diversity has been demonstrated by other authors (Alcaraz-Segura et al., 2006; Paruelo et al., 2001). However, the results shown here indicate for the first time the relevance of internannual variability on ecosystem functioning to define their intrinsic heterogeneity. This novel approach allows including the effects of climate variability on ecosystem dynamics, thus enhancing our understanding of ecosystem functional diversity. The characterization of ecosystem functioning spatial heterogeneity demonstrated the presence of larger quantity and heterogeneity of EFTs than found in previous works (Alcaraz-Segura et al., 2013; Paruelo et al., 2001). This difference could be attributed to the use of several additional ecosystem functional variables, mainly to the use of the interannual variability of ecosystem functioning. On the other hand, a higher quantity and heterogeneity of EFTs implies higher functional homogeneity within each EFT. This could be relevant for the implementation of strategies for natural resource management and biodiversity conservation.

In the Argentina Pampas, EFTs with moderate annual productivity were the most spatially representative. This situation is expected due to the combinations of variation patterns of temperature, moisture and radiation (Jolly et al., 2005; Nemani et al., 2003). These EFTs probably correspond to dynamic transitions between different land use categories.

The low agreement found between both our approach and Matteucci's (2012) could be interpreted as a lack of link between structure and function of the ecosystems, a relationship that has been widely supported in the literature of the last decades (Hooper et al., 2005; Loreau et al., 2001). Rather, our results are associated with the great ability of the functional approach to record rapid changes observed in the anthropized ecosystems. On the other hand, they indicate that it is not possible to establish a clear relationship between both approaches because they are product of different methodologies. Both the criteria and the level of clustering to define homogeneous ecosystems are also different. Another explanation for the differences between structural and functional approaches could be the effects of land cover changes which are strong in some places of the region (Baldi and Paruelo, 2008; Guerschman et al., 2003; Lara and Gandini, 2014).

The methodology used in this paper to characterize the regional patterns of ecosystem functional diversity has the advantage of reducing the degree of subjectivity in comparison with other approaches. The use of interannual variability on ecosystem functioning is a way to include the effects of climate variability. This methodology may be applied either at a global scale or at different scales depending on the objectives, even with a different remote-sensing dataset or time series. Despite efforts to conserve the biological diversity, species and their ecosystems are still being lost at a very fast rate (Pettorelli et al., 2016). This scenario requires indicators that respond quickly to the disturbances and may be comparable across regions and scales. The knowledge of spatial patterns of ecosystem functioning in the Argentina Pampas is a first approach in this line.

5. Conclusions

The characterization of EFTs at a regional scale is a key feature for understanding the integrity of ecosystem functional diversity and ecosystem services. Based on carbon gains derived from 14-year NDVI time-series, we found nine EFTs that demonstrate the high ecosystem functional diversity in the Argentina Pampas.

In this study, we demonstrated the relevance of interannual variations for mapping ecosystem functioning that may be applied at different scales. The results obtained with this novel approach should be a baseline scenario for the implementation of strategies for natural resource management and biodiversity conservation and for evaluating the effects of environmental and anthropogenic changes.

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Highlights

- Annual productivity was the most representative indicator of the total variance.
- Interannual variability on ecosystem functioning showed relevance to define their heterogeneity.
- Results highlight the importance of climate variability for ecosystem dynamics monitoring.