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Can we Monitor Height of Native Grasslands in Uruguay with Earth Observation?

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Received: 4 June 2019; Accepted: 30 July 2019; Published: 1 August 2019

Abstract: In countries where livestock production based on native grasslands is an important economic activity, information on structural characteristics of forage is essential to support national policies and decisions at the farm level. Remote sensing is a good option for quantifying large areas in a relative short time, with low cost and with the possibility of analyzing annual evolution. This work aims at contributing to improve grazing management, by evaluating the ability of remote sensing information to estimate forage height, as an estimator of available biomass. Field data (forage height) of 20 commercial paddocks under grazing conditions (322 samples), and their relation to MODIS data (FPAR, LAI, MIR, NIR, Red, NDVI and EVI) were analyzed. Correlations between remote sensing information and field measurements were low, probably due to the extremely large variability found within each paddock for field observations (CV: Around 75%) and much lower when considering satellite information (MODIS: CV: 4%–6% and Landsat:CV: 12%). Despite this, the red band showed some potential (with significant correlation coefficient values in 41% of the paddocks) and justifies further exploration. Additional work is needed to find a remote sensing method that can be used to monitor grasslands height.

Keywords: remote sensing; livestock; forage; MODIS; campos

1. Introduction

Native grasslands are one of the largest ecosystems in the world with an estimated cover area of 40 to 50 million square kilometers [1,2]. They are defined as natural ecosystems dominated by naturally occurring grasses and other herbaceous species with the possible presence of woody species, used mainly for grazing by livestock and wildlife [3].

As population increases, grasslands are becoming important contributors to human food supply (meat and milk), while providing other important ecosystem services, such as carbon sequestration, genetic material storage, water quality, and soils conservation [4,5].

The Río de la Plata grasslands (located between 28° S to 38° S) are among the world´s largest temperate-subtropical grasslands, covering the central-eastern part of Argentina, all of Uruguay, and southern Brazil. These grasslands are subdivided into "pampas" and "campos" [6]: The former are temperate treeless grasslands located in eastern and central Argentina on flat and fertile plains, humid to arid climate, with warm summers and mild winters [3]. "Campos" are grasslands consisting mainly of grasses, along with other herbaceous species, small shrubs, and occasional trees. They occur on undulating and hilly landscapes, with variable soil fertility, in sub-tropical humid climate, warm in summer and mild in winter, found in Uruguay, southern Brazil, and north-eastern Argentina [3].

In Uruguay, livestock production is mainly based on extensive grazing of native grasslands, which represent over 65% of the country´s total area. Uruguay has a wide diversity of soil types [7] and, as a consequence, its grasslands are heterogeneous including tens of species per m^2 [8,9] and a total of more than 350 registered species [10]. These grasslands have a predominance of summer growing species (C4) with an increase in frequency of cold-season species (C3) during autumn and winter [7]. Considering that warm-season species are responsible of the highest forage production (in spring and summer), and that this is the season with highest rainfall variability, the risks related to drought are very high [7].

In environments with large variation in herbage production, due to seasonal and interannual variability in rainfall and temperature, the optimal stocking rate needed to reach a specific performance target varies widely among seasons and years [11–13]. The control of grazing intensity through the management of stocking rate is an important tool to regulate the amount of solar energy captured and converted into beef production. Within this context, herbage allowance (HA), defined as kilograms of herbage dry matter per kilogram of animal body weight [3,14], may be more useful than stocking rate for managing the grazing process [15]. Managing HA requires herbage mass estimation, or a proxy like herbage height [16].

Information related to structural characteristics (herbage height or biomass) of native grasslands is essential to support management decisions, not only at the farm level but also at national and regional levels, to inform policy making. This results in demands on researchers to generate "low cost, appropriate and timely information that can be provided to farmers to support their decision-making" [17]. Bearing in mind that existing field methods are labor-intensive and time-consuming, it is difficult to extend HA control to large areas. In this context, remote sensing monitoring is a promising option for quantifying large areas in a relative short time at a comparatively low cost and offering the possibility of analyzing historical data series.

Considerable research has been conducted to monitor indicators of the vegetation condition [18] and, more specifically, to characterize grasslands functioning. Thus, remote sensing has been used to estimate above ground net primary production (ANPP), with the advanced very high-resolution radiometer (AVHRR-NOAA) and the moderate-resolution imaging spectroradiometer (MODIS) [19–24]. Annual grassland biomass has also been estimated using different satellite sensors (MODIS, SPOT, and AVHRR) with good results in Northern China [25] and in the Sahel [26].

Other ecosystem's structure and function attributes have also been related to vegetation indexes coming from Earth observation. In the Patagonia steppes, Gaitan et al. [27] assessed the relationship between cover and species richness with nine different vegetation indicators. The authors showed that NDVI explained 30%–40% of the total variability found in these ecosystem attributes. In the arid southwest grasslands of North America, the total herbaceous vegetation cover (green and senescent), height, and biomass estimated using the soil adjusted total vegetation index (SATVI) for cover and the near infrared band from Landsat for height and biomass, was highly correlated with observed information [28].

Grasslands biophysical parameters, mostly considered in a season or in annual base, have been retrieved from Earth observation for many years. Recently, the modelling approaches are evolving to more complex, robust, and efficient ones [29]. Also, some studies included higher-resolution sensors such as Sentinel 2 or modern technologies such as radar (active sensor) [30–32]. However, more research is needed to accurately estimate the intra-annual performance of some biophysical variables as biomass or height.

In this work, we tried to estimate observed grasslands behavior as a "photograph" of what was available in terms of forage height at different time steps along the year. This approach differs from estimating the height as the annual or seasonal accumulation of biomass. Our approach seems to be particularly important for improving management of livestock production systems. We also analyzed intra paddock variability at different spatial scales.

In this context, the objective of this study was to contribute to improve grazing management by evaluating the ability of remote sensing information to estimate forage height (as an estimator of available biomass) at paddock scale.

2. Materials and Methods

2.1. Study Area

The study was carried out on 11 commercial farms located in Uruguay (30°–35° S, 53°–59°W), South America. Seven of them were located in the eastern region and the other four in the central zone of the country (Figure 1).

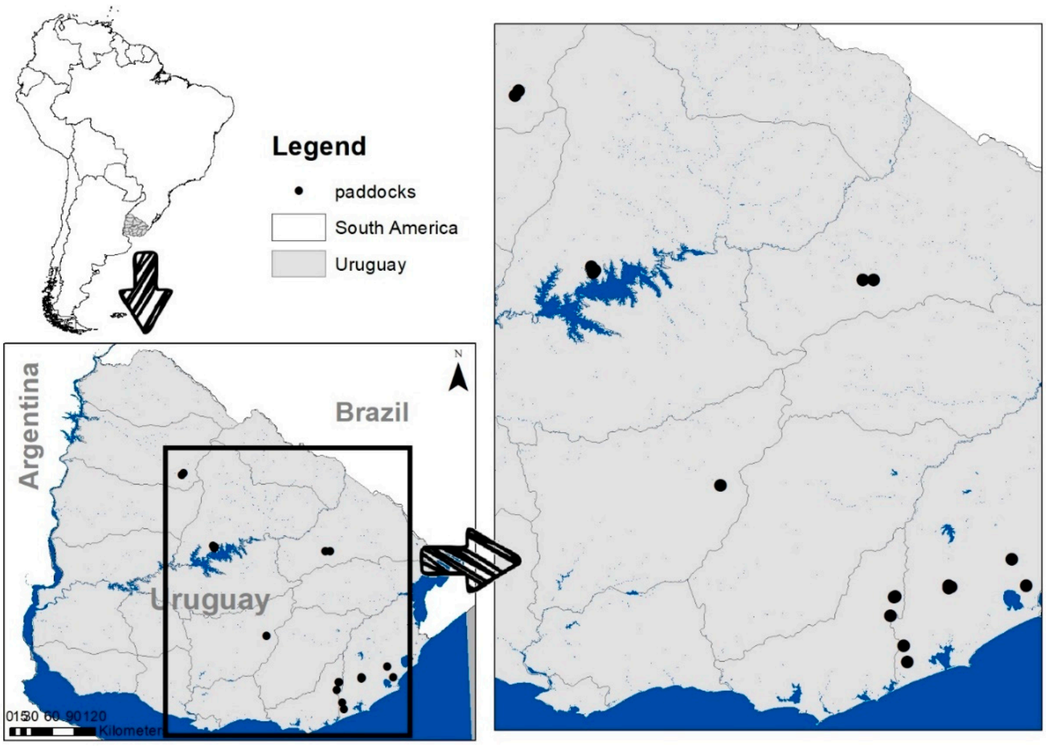

Figure 1. South America map highlighting Uruguay (up-left corner) and paddock´ location in Uruguay (bottom left corner and right).

2.2. Data

2.2.1. Farm Data

A total of 20 natural grasslands paddocks under grazing conditions, identified as 1 to 20, were analyzed. Six of the farms had only 1 analyzed paddock (paddocks 3, 4, 7, 14, 19, and 20), four farms had 2 paddocks, and one farm had 6 evaluated paddocks. The sizes varied between 12 has and 258 has. (Table 1).

Table 1. Area of the 20 paddocks analyzed in this study. Paddocks were designated from 1 to 20. Letters from A to K designate farms.

Paddock Number	Area (has)
3(B), 4(A), 7(C), 9(E), 10 (E), 19(D), 20(F)	12–50
8 (E), 11 (E), 15 (G), 16 (G), 17 (H), 18 (H)	51–100
1 (I), 2 (I), 5 (K), 12 (E), 13 (E), 14(J)	101–150
6 (K)	>151

Farm data (forage height) were collected between October 2012 and December 2015 every 40–50 days, two times per season, in each of the 20 paddocks under grazing conditions, with a total of 322 data points. Each forage height estimation was collected using the standard "comparative yield method" [33] by trained experts, collecting 100 to 300 sampling points in a systematic procedure to evenly cover the paddock area and decreasing the sampling error as the observation number increased. In every case, and in order to avoid biases associated with the different users, every sample was taken by trained assistants and researchers.

Five to seven reference quadrats of 50 cm × 50 cm were located to cover height heterogeneity, and height was measured in five points for every quadrat. In these same quadrats, a five-level scale was defined, where "1" was the lowest height and "5" was the highest. These scale samples were transformed into height measures by applying the linear regression equations resulting from the analysis of the measurements of forage height and estimated scale within the reference quadrats for each paddock. After that, more than 100 points were sampled, and each observer had to assign a scale value to each point. A "0" value was assigned when bare soil was identified. Finally, we used the regression equation explained above to convert scaled values into height.

The forage average height, median, mode, and maximum values were estimated for each paddock at each date.

Each paddock was sampled on average 16 times (between three and 23) during the analysis period. When variables of every paddock were analyzed together, the 20 paddocks were included, but when each paddock was analyzed individually, paddocks with less than 10 sampling dates were discarded (paddocks 6, 8, and 10). Outliers due to annotations mistakes or sampling errors were removed from the analysis.

2.2.2. Satellite Data

Spatial and temporal resolutions are critical when grasslands biophysical parameters have to be monitored. Analyses were conducted based on MODIS information downloaded from Earth Data website (https://search.earthdata.nasa.gov/search). We selected MODIS products because of their good temporal resolution (daily), the relatively good spatial resolution (250 m, 500 m), and the possibility of easily escalating to regional or national level with the same image (only one Path and row for Uruguay). In addition to this, higher-resolution sensors (Landsat or Sentinel 2) have no daily information or had no information available for Uruguay for the period when the field data were obtained (Sentinel 2).

We worked with ESRI®ArcGis 10.4 for Desktop on MODIS sinusoidal coordinate system, reprojecting the farm paddocks originally generated on WGS84.

Relations between spatial data at different temporal and spatial resolutions, and field data, were analyzed to achieve the objective of the research. We used composite images because of the practicality and daily information in order to have the data closest to the field measurement date, to have every pixel of the same date and to be able to choose nearby date due to the assiduous presence of cloud cover in some part of the country and time of the year.

We computed the weighted average of satellite pixels within each paddock. We considered the trade-off between size and purity, trying to select a sufficient number of pure pixels [34]. In some cases, because of the shape of the paddocks, no pure pixels fitted in it. In those cases, we used the weighted average (percentage of the area within the paddock) estimated only with the non-pure pixels, which centroid fitted in that paddock (more than 80% of the pixel was located inside the paddock).

Composite MODIS data

From composite products and for the analyzed period, we used:

- MOD13Q1, 250 m V006 [35]. We selected the middle infrared band (MIR), near infrared band (NIR), and red bands; and the normalized difference vegetation index (NDVI) and enhanced vegetation index (EVI).
- MCD15A3H, 500 m V006 [36]. We used fraction of photosynthetically active radiation (FPAR) and leaf area index (LAI). According to Myneni et al. (2015), in this context and for this product, "LAI is defined as the one-sided green leaf area per unit ground area in broadleaf canopies and as one-half the total needle surface area per unit ground area in coniferous canopies. FPAR is defined as the fraction of incident photosynthetically active radiation (400–700 nm) absorbed by the green elements of a vegetation canopy".

Quality bands of composite products were also checked.

Daily MODIS data

We extracted daily information from October 2012 to December 2015 of every paddock. We used the bands and index described as follows:

- MOD09GQ (GQ). MODIS Terra/Aqua Surface Reflectance 250 m [37]. We selected the near infrared (NIR) and red bands; and estimated NDVI (NIR-Red/NIR+Red).
- MOD09GA (GA). MODIS Terra/Aqua Surface Reflectance 500 m. [37]. We selected MIR, NIR, and red bands; and estimated NDVI (NIR-red/NIR+red) and Normalized Difference Water Index, NDWI (NIR-MIR/NIR+MIR).

In order to select the MOD09 daily images, we analyzed zenith and azimuth angles for the sun and sensor positions. For each paddock, we selected cloud-free images that were closest to the field measurement date (no more than 15 days before or 15 days after). Considering that most of the chosen images had similar solar and sensor zenith angles, we avoided dates where sun and sensor were at the same side (azimuth angles with the same sign) because of the hot spot effect. We finally tried to select similar angles to have equivalent images conditions.

We also analyzed quality bands in order to identify the best data for the studied dates and paddocks. In this analysis, we found quality data that indicate good quality values, but when we visually checked the images, clouds were detected. Because of this, we also visually analyzed each selected image, to confirm that no clouds were present over the paddocks, in order to use them properly.

- MCD43A4 (Nbar). MODIS/Terra and Aqua Nadir BRDF (bidirectional reflectance distribution function) adjusted reflectance (NBAR), 500 m, V006 [38]. We selected MIR, NIR, and red bands; and estimated NDVI and NDWI.

Landsat data

Landsat images were only used to verify variability at different spatial scales due to their low temporal resolution (16 days) and the consequent high probability of cloud cover, which makes it more difficult to find available data (cloud free) for each sampling date. We downloaded and analyzed Landsat 8 (30 m spatial resolution) images (OLI/TIRS Level-2 Data Products—Surface Reflectance) from Earth Explorer website (https://earthexplorer.usgs.gov/) [39]. We only considered images visually identified as without clouds over the paddocks, within the period of 15 days before and 15 days after the field measurements date. We arbitrarily selected one band (NIR). Weighted average and standard deviation of Landsat NIR was estimated for each paddock.

We also estimated the standard deviation of NIR from both MOD09 products (GA and GQ) and MOD13Q1 for each paddock.

2.2.3. Data Analysis

We compared and correlated data obtained at paddock level with satellite data in order to identify variables that can predict native grasslands height and/or available biomass. We first analyzed the relationship between the variables by pairs and scatterplot's linearity was checked. An example of the analysis of median height vs. MODIS daily variables for all the paddocks is shown in Figure 2.

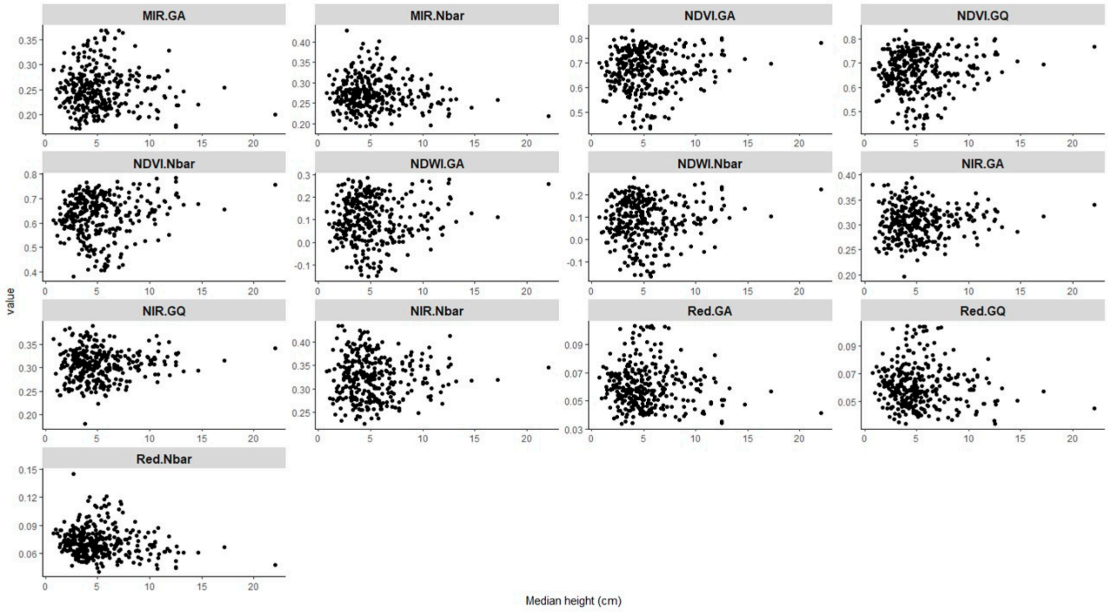

Figure 2. Scatterplot of median height (cm) in the x axes and MODIS satellite information in the y axes for all the analyzed paddocks. MIR: Middle infrared band, NIR: Near infrared band, Red: Red band, NDVI: Normalized difference vegetation index, EVI: Enhanced vegetation index. Nbar (MODIS/Terra and Aqua Nadir BRDF (bidirectional reflectance distribution function) adjusted reflectance (NBAR), 500 m), GA (MODIS Terra/Aqua Surface Reflectance 500 m), and GQ (MODIS Terra/Aqua Surface Reflectance 250 m) refer to the MODIS daily products analyzed.

Pearson coefficient of correlation was estimated for every paddock jointly and for each individual paddock. Spearman coefficient of correlation was also checked, reaching very similar values.

Variability within the paddocks was analyzed as well. Coefficient of variation, for each sampling date within paddocks, was analyzed for height measurement and pixels satellite information.

We worked with ESRI®ArcGis 10.4 for Desktop, R version 3.4.1, and R Studio software (Version1.0.143) to analyze farm measurements distributions and correlations.

3. Results

3.1. Farm Data

Figure 3 presents the results of height measurements for each paddock for the period October 2012–December 2015, showing the seasonal pattern. Regarding the inter-date variability in height, results showed differences in the observed measurements distribution for each paddock within dates. The average inter date coefficient of variation (CV) of the 17 paddocks selected for individual analysis was 76% (range: 53%–100%).

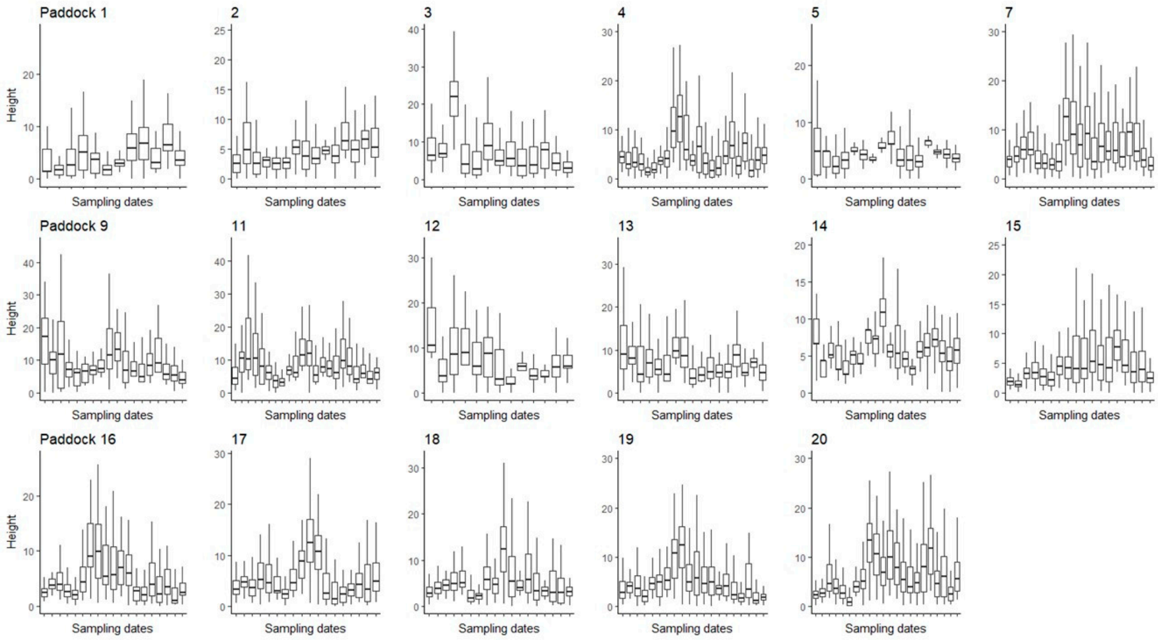

Figure 3. Height (cm) boxplot showing the distribution of observed data of each one of the 17 individually analyzed paddocks. Paddocks with less than 10 sample dates were discarded (paddock 6, 8, and 10). Sampling dates, from October 2012 to December 2015, are different according to each paddock.

3.2. Composite MODIS Data

Regarding composite images, Pearson correlations between median height and satellite information (FPAR, LAI, MIR, NIR, Red channel, NDVI, and EVI) for all the paddocks, showed non-significant values (lower than 0.1).

The correlation between median height and MODIS composite images for each paddock individually evidenced different performances depending on the paddock (Table 2).

Table 2. Pearson correlation coefficient between median height and composite MODIS satellite variables for every analyzed paddock (P). Significant ($p < 0.05$) correlation coefficient values are highlighted in grey. FPAR: Fraction of photosynthetically active radiation, LAI: Leaf area index, MIR: Middle infrared band, NIR: Near infrared band, Red: Red band, NDVI: Normalized difference vegetation index, EVI: Enhanced vegetation index.

P	FPAR	LAI	MIR	NIR	Red	NDVI	EVI
1	0.024	0.204	−0.335	0.041	−0.248	0.201	0.141
2	0.084	0.013	−0.355	0.042	−0.306	0.244	0.200
3	0.217	0.305	−0.606	0.173	−0.514	0.428	0.307
4	−0.605	−0.376	0.030	0.290	0.087	0.076	0.246
5	0.324	0.458	−0.182	0.289	−0.305	0.354	0.349
7	0.180	0.225	−0.094	0.079	0.146	0.029	0.067
9	0.603	0.468	−0.537	0.306	−0.481	0.571	0.543
11	0.555	0.363	−0.499	0.253	−0.323	0.411	0.390
12	−0.076	−0.036	0.091	0.228	0.119	−0.043	0.042
13	0.444	0.274	−0.402	0.229	−0.387	0.409	0.406
14	0.247	0.263	−0.471	0.285	−0.324	0.351	0.353
15	0.328	0.250	−0.407	−0.188	−0.380	0.240	−0.001
16	−0.235	−0.237	−0.728	0.059	−0.528	0.490	0.306
17	−0.478	−0.282	−0.400	0.065	0.130	0.370	0.335
18	−0.574	−0.390	0.003	0.098	0.571	−0.261	−0.002
19	0.447	0.363	−0.163	0.483	−0.190	0.543	0.588
20	−0.367	−0.282	−0.218	−0.063	−0.131	0.083	0.018

The remote-sensed variable that showed largest number of paddocks with significant and consistent (negative) correlation coefficient values, was MIR (Table 2). FPAR, despite having one more significant correlation values, showed no consistent results (positive in some cases and negative in others).

3.3. Daily MODIS Data

We first analyzed the correlation of remote sensing MODIS variables (MIR, NIR, Red channel, NDVI, and NDWI) with field information from all farms considered together. From this analysis, Pearson correlation coefficient indicated no significant correlation between observed data and satellite information (Table 3).

Table 3. Pearson correlation coefficients between height (median, average, mode, and maximum value) and daily MODIS satellite variables for all paddocks.

	H Median	H Average	H Mode	H Maximum
MIR (GA product)	−0.032	−0.018	−0.013	0.034
NIR (GA product)	0.090	0.070	−0.003	0.036
Red (GA product)	−0.085	−0.067	−0.041	0.008
NDVI (GA product)	0.108	0.087	0.037	0.012
NDWI (GA product)	0.079	0.058	0.013	−0.002
NIR (GQ product)	0.083	0.058	0.009	0.029
Red (GQ product)	−0.092	−0.077	−0.047	0.001
NDVI (GQ product)	0.112	0.092	0.047	0.016
MIR (Nbar product)	−0.087	−0.092	−0.008	−0.056
NIR (Nbar product)	0.014	−0.011	0.000	−0.051
Red (Nbar product)	−0.163	−0.156	−0.070	−0.092
NDVI (Nbar product)	0.136	0.121	0.060	0.051
NDWI (Nbar product)	0.081	0.070	0.011	0.016

Although all correlation coefficient values were low, they were higher when the median was considered (Table 3). This justifies the decision to consider the median as the most representative statistic of the observed values in the paddocks.

We then analyzed each paddock individually and assessed the correlation of all the satellite variables (MIR, NIR, Red channel, NDVI, and NDWI) with the field measurements. Pearson correlation coefficients with all satellite variables were generally low and, in some cases, not consistent, with positive correlations in some paddocks and negative in others. Despite this, there were some individual paddocks that had significant correlation ($p < 0.05$) with most of the analyzed satellite information. The highest coefficient was found with NDWI of MODIS GA product (r = 0.68, $p = 0.002$) but the Red channel of MODIS Nbar product have the highest number of paddocks with significant correlation values (7 paddocks from a total of 17). A linear relationship between satellite information and height median is shown in Table 4. No daily satellite information had significant correlation in every paddock together (Table 4).

Table 4. Pearson correlation coefficients between height and daily MODIS satellite variables for every analysed paddock (P). Significant ($p < 0.05$) correlation coefficient values are shaded in grey. MIR: Middle infrared band, NIR: Near infrared band, Red: Red band, NDVI: Normalized difference vegetation index, NDWI: Normalized difference water index. Nbar (MODIS/Terra and Aqua Nadir BRDF (bidirectional reflectance distribution function) adjusted reflectance (NBAR), 500 m), GA (MODIS Terra/Aqua Surface Reflectance 500 m), and GQ (MODIS Terra/Aqua Surface Reflectance 250 m) refer to the MODIS daily products analyzed.

P	MIR, GA	NIR, GA	Red, GA	NDVI, GA	NDWI, GA	NIR, GQ	Red, GQ	NDVI, GQ	MIR, Nbar	NIR, Nbar	Red, Nbar	NDVI, Nbar	NDWI, Nbar
1	0.002	−0.074	−0.010	−0.003	−0.027	−0.036	−0.029	0.021	−0.008	0.039	−0.001	0.000	0.014
2	0.246	0.122	−0.002	0.039	−0.105	0.135	−0.012	0.052	−0.214	−0.323	−0.161	0.015	−0.020
3	−0.525	0.314	−0.431	0.377	0.522	0.361	−0.333	0.329	−0.539	0.139	−0.645	0.500	0.492
4	−0.036	0.014	0.014	0.001	0.036	0.018	−0.080	0.069	0.062	0.028	−0.174	0.168	−0.019
5	−0.256	0.383	−0.429	0.464	0.372	0.377	−0.429	0.441	−0.067	0.362	−0.309	0.432	0.359
7	−0.180	0.258	−0.342	0.352	0.290	0.229	−0.293	0.323	0.071	0.137	−0.283	0.225	0.081
9	−0.546	0.519	−0.574	0.615	0.679	0.479	−0.558	0.597	−0.438	0.460	−0.547	0.619	0.600
11	−0.453	0.450	−0.467	0.494	0.520	0.386	−0.445	0.466	−0.349	0.422	−0.445	0.530	0.509
12	0.115	0.074	0.140	−0.106	−0.062	0.022	0.166	−0.140	0.120	0.002	0.040	−0.031	−0.103
13	−0.116	0.523	−0.136	0.246	0.334	0.481	−0.159	0.263	−0.358	0.192	−0.420	0.397	0.397
14	−0.288	0.276	−0.252	0.277	0.323	0.280	−0.226	0.261	−0.519	−0.015	−0.511	0.327	0.309
15	−0.425	−0.160	−0.472	0.257	0.136	−0.121	−0.301	0.167	−0.262	−0.002	−0.351	0.212	0.192
16	−0.482	0.371	−0.272	0.364	0.499	0.366	−0.221	0.315	−0.579	0.160	−0.607	0.533	0.576
17	−0.335	0.295	−0.390	0.469	0.430	0.283	−0.367	0.444	−0.172	0.202	−0.576	0.609	0.504
18	−0.268	0.211	−0.447	0.408	0.288	0.204	−0.475	0.415	−0.278	0.051	−0.420	0.353	0.342
19	−0.482	0.351	−0.555	0.523	0.501	0.328	−0.610	0.556	−0.257	0.250	−0.594	0.584	0.467
20	−0.061	−0.241	0.053	−0.097	−0.059	−0.162	0.020	−0.052	−0.266	−0.346	−0.268	0.008	−0.106

After analyzing these correlations and in order to check if any satellite information could provide an estimate of increase or decrease in height, we also checked for correlations between height and satellite information, estimating the differences between one date and the previous one (delta value). Pearson coefficients for each paddock and their statistical significance are shown in Table 5.

Table 5. Pearson correlation coefficients between delta median height (difference between one date and the previous one) and delta daily MODIS satellite variables for every analyzed paddock (P). Significant ($p < 0.05$) correlation coefficient values are highlighted in grey. MIR: Middle infrared band, NIR: Near infrared band, Red: Red band, NDVI: Normalized difference vegetation index, NDWI: Normalized difference water index. Nbar (MODIS/Terra and Aqua Nadir BRDF (bidirectional reflectance distribution function) adjusted reflectance (NBAR), 500 m), GA (MODIS Terra/Aqua Surface Reflectance 500 m), and GQ (MODIS Terra/Aqua Surface Reflectance 250 m) refer to the MODIS daily products analyzed.

P	MIR, GA	NIR, GA	Red, GA	NDVI, GA	NDWI, GA	NIR, GQ	Red, GQ	NDVI, GQ	MIR, Nbar	NIR, Nbar	Red, Nbar	NDVI, Nbar	NDWI, Nbar
1	−0.316	0.479	−0.323	0.457	0.514	0.522	−0.339	0.476	−0.305	0.412	−0.283	0.410	0.510
2	−0.093	0.597	−0.380	0.458	0.379	0.568	−0.373	0.463	−0.470	−0.031	−0.419	0.379	0.385
3	−0.591	0.201	−0.541	0.392	0.637	0.242	−0.408	0.336	−0.499	0.106	−0.604	0.500	0.550
4	−0.134	0.092	−0.205	0.194	0.143	0.138	−0.216	0.224	−0.001	0.267	−0.331	0.386	0.158
5	−0.223	0.518	−0.314	0.462	0.493	0.552	−0.336	0.462	−0.291	0.386	−0.392	0.527	0.540
7	0.009	0.051	−0.183	0.188	0.047	0.010	−0.093	0.110	0.319	0.027	0.106	−0.125	−0.317
9	−0.225	0.480	−0.301	0.403	0.490	0.447	−0.281	0.380	−0.255	0.320	−0.342	0.378	0.348
11	−0.108	0.506	−0.266	0.374	0.361	0.467	−0.258	0.364	−0.254	0.305	−0.342	0.377	0.329
12	−0.072	0.251	−0.154	0.189	0.195	0.217	−0.139	0.172	−0.015	0.296	−0.272	0.302	0.145
13	−0.425	0.501	−0.444	0.532	0.666	0.485	−0.482	0.567	−0.632	0.366	−0.623	0.629	0.706
14	−0.063	0.404	−0.173	0.281	0.258	0.367	−0.108	0.218	−0.260	−0.045	−0.389	0.279	0.135
15	−0.603	0.019	−0.293	0.232	0.348	0.056	−0.176	0.167	−0.223	0.084	−0.022	0.076	0.270
16	−0.173	0.240	−0.132	0.190	0.293	0.277	−0.147	0.205	−0.143	0.186	−0.254	0.355	0.370
17	−0.181	0.300	−0.282	0.406	0.351	0.251	−0.306	0.409	−0.065	0.301	−0.371	0.539	0.477
18	−0.153	0.369	−0.221	0.296	0.329	0.388	−0.260	0.323	−0.050	0.114	−0.248	0.267	0.188
19	−0.038	0.160	−0.320	0.296	0.133	0.205	−0.350	0.353	0.158	0.286	−0.148	0.363	0.232
20	−0.094	0.075	−0.007	0.012	0.114	0.145	−0.046	0.064	−0.256	−0.105	−0.293	0.145	0.077

There were four indices that showed the largest number of paddocks with significant correlations: Delta NIR (GA) in four paddocks and Delta NDWI (GA), Delta NIR(GQ), and Delta NDVI (Nbar) in three paddocks. These new correlations (delta values, Table 5) were no better than correlation showed in Table 4 despite having the higher correlation value (−0.706, $p < 0.05$).

Considering the information of all paddocks considered together, the delta values presented better results than red channel, NIR, MIR, NDVI, and NDWI values, obtaining the best correlation value between delta height and delta NDWI (MODIS GA product) (Figure 4). It is worth mentioning that these better correlation values are probably due to two delta height values (circled in red in Figure 4), which are likely very influential statistically and resulted in improved correlation.

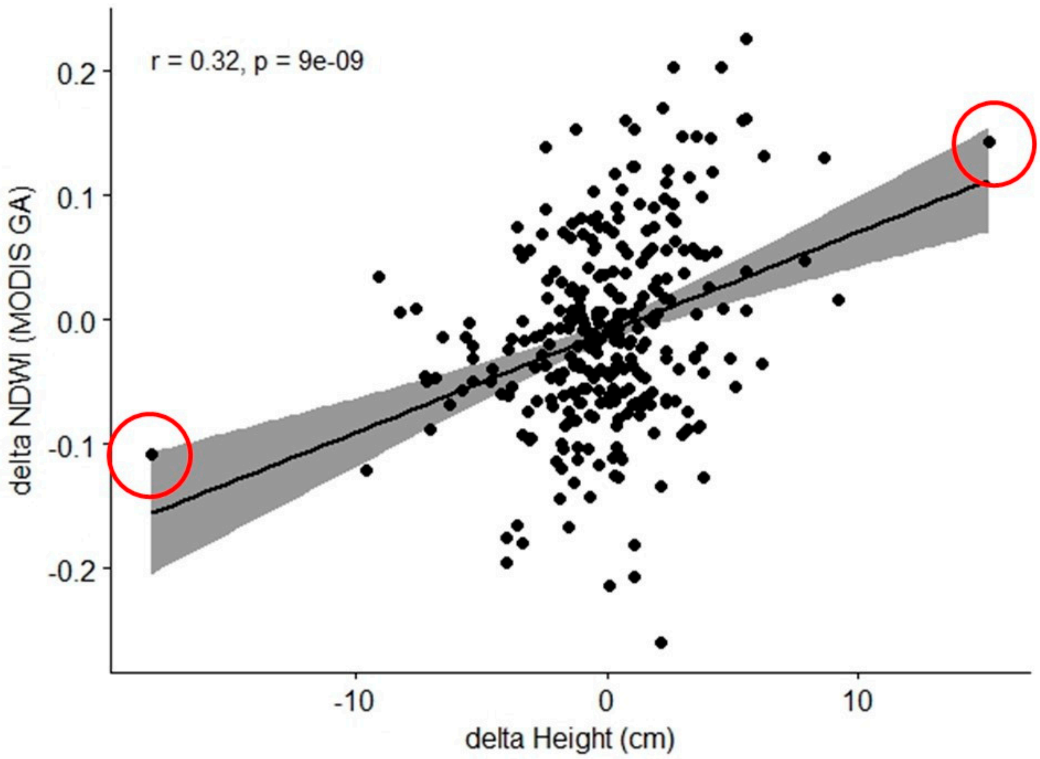

Figure 4. Linear correlation between delta median height and delta NDWI from MODIS GA product, considering the whole field information together. Pearson correlation value and significance are r = 0.32, $p < 0.001$. The tow influential data points are circled in red.

3.4. Variability

Analyzing variability and bearing in mind that farm measurements have coefficients of variation within paddocks of around 75% on height, we estimated the coefficient of variation of the satellite information (Table 6) to check variability at different spatial scales (Landsat and MODIS).

Paddocks 4, 7, and 10 have no MODIS (GA) information because of their shape and size; only one centroid of a pixel fitted the paddock.

Satellite information evidenced much smaller variability than field measurements with coefficients of variation for MODIS around 4% for 500 m resolution products, between 5% or 6% in 250 m resolution products, and 12% for Landsat (30 m spatial resolution).

Table 6. Average of the coefficient of variation (CV) of satellite information within paddocks on the considered dates and the standard deviation (SD) of those estimations for every paddock (P).

P	Dates Considered	Landsat		MODIS GQ		MODIS Comp		MODIS GA	
		CV	SD	CV	SD	CV	SD	CV	SD
1	10	12.04	1.44	6.27	0.95	6.23	0.83	5.89	2.15
2	12	9.89	4.05	4.41	6.59	4.49	2.59	1.56	0.58
3	8	15.32	13.12	2.92	1.74	4.15	1.70	2.88	0.86
4	9	10.89	3.27	5.01	6.75	5.38	1.78		
5	9	18.10	10.67	8.64	1.67	11.43	5.11	6.87	3.52
6	4	11.95	11.49	9.18	2.07	8.09	2.45	8.89	2.55
7	10	15.95	6.78	4.86	1.66	4.75	1.18		
8	8	8.43	3.08	4.23	2.10	5.64	1.37	9.50	8.66
9	12	9.94	7.33	3.15	1.78	3.56	1.56	2.16	1.63
10	2	4.76	1.06	1.62	0.27	2.21	0.09		
11	13	7.79	2.34	3.27	1.53	4.03	2.19	2.04	1.24
12	11	8.95	1.88	2.60	1.28	4.72	2.08	1.35	0.93
13	14	8.63	2.86	3.22	1.10	5.09	1.93	3.23	1.10
14	14	14.98	7.45	7.07	3.20	7.74	2.75	4.01	3.93
15	11	18.44	11.39	3.96	1.04	4.52	0.76	2.86	1.85
16	12	14.78	4.68	6.51	1.37	6.71	1.67	6.00	2.04
17	6	14.12	8.52	5.71	3.60	8.96	5.75	4.52	2.51
18	6	11.94	6.12	6.79	2.94	9.46	5.54	1.97	1.71
19	11	19.57	8.56	6.40	4.10	7.55	3.70		
20	8	8.09	7.92	3.37	1.82	4.46	3.11	1.26	1.01

4. Discussion

In agreement with previous studies that described native grassland variability [40], field measurements were extremely variable within the paddocks for each sampling date, with coefficients of variation around 75%. In most paddocks, this heterogeneity was even higher as the height increased, as shown in Figure 2, where the size of the boxes is larger when the values of the median are higher. This is probably due to the small-scale botanical and structural heterogeneity of this environment, but also because of variation in livestock management and in climate conditions. The amount of variability also showed differences between dates, probably associated with seasonal species composition. On the other hand, as satellite information provides an average value at a pixel resolution (500 m, 250 m, 30 m), it is expected to have much less variability but, differing to what we anticipated, showed no strong differences between these spatial resolutions. Thus, Landsat 8 (with spatial resolution of 30 m), could not represent the variability of native grassland more accurately than MODIS. Therefore, it can be expected that using other sensors with a resolution that is slightly higher, such as Sentinel 2, would not result in a better characterization of this variability either. Although it could be worth to check this fact, we probably must appeal to sensors of much higher resolution (1 m or centimeters) or non-optical ones (radar).

When we compared these extremely variable field measurements with MODIS satellite information, poor correlations were found. MODIS composite or daily variables seem to be not sensitive to grassland height variations. Considering the median height of every date and paddock, the minimum value was 1.4 cm and the maximum was 22 cm (Figure 3 boxplots), while satellite band reflectance values from GA product vary only from 0.17–0.37 for MIR, 0.20–0.39 for NIR, and 0.03–0.1 for the red band. Regarding the vegetation indices, NDVI varied from 0.43 to 0.83 and the NDWI from −0.15 to 0.28. This is consistent with results found in the semi-arid Sahel by Olsen et al. [26], who concluded that an increase in NDVI over time cannot always represent an increase in herbaceous biomass. This could be due to the fact that NDVI saturates at high biomass or leaf area index.

In contrast to what was found on monospecific pastures of alfalfa and grass (tall fescue), where good correlations are reported between height and several vegetation indices [41], our study showed that no daily or composite MODIS satellite information could explain height observed behavior in the natural grasslands of every paddock and date. This could probably be due to the hundreds of species present in native grasslands that result in such a heterogeneous environment, and/or to the presence of non-photosynthetically active plant material that could influence the signal captured by remote sensing sensors. For example, in paddocks 4, 17, and 18 (Table 2), the correlation between height and FPAR was negative, opposing what we expected. A similar situation occurred in paddock 18 with a positive correlation between height and red band. Careful consideration of the results at individual paddocks revealed that in all cases mentioned above, we found one very influential point with a high value of height and low value of FPAR (and high value of red band). This could probably be due to a situation with high biomass and a large proportion of senescent material. In general, MODIS composite information (MOD13Q1 and MCD15A3H) did not show good results either, and only MIR appeared as a variable worthy of further exploration in future work.

Analyzing paddocks individually, red band was the most promising variable (Table 4). Some paddocks had high and significant correlation values with several satellite variables (NIR, MIR, red band, NDVI, NDWI). Paddock 9, 11, and 19 showed significant correlations in more than 9 (out of a total of 13) daily remote sensing variables; paddock 13 a total of 8 with daily delta value; and paddock 9 and 19 more than 4 (from a total of 7) with composite images. Other paddocks had no correlation with any variables (paddock 1, 7, 12, and 20). Taking into consideration only the significant values, the sign (+ or −) of Pearson correlation coefficient values result as we expected for all the plots (positive relation between height and NIR, NDVI, and NDWI; and negative relation with MIR and red band).

On the other hand, changes in height and in satellite variable values from one date to the next (delta values) only showed better results than single date values when NIR (GA) was used (Table 5). There were some paddocks that had relatively good correlations (Person correlation values >0.6) between height and one or more of the different satellite variables such as MIR and NDWI of the GA MODIS product and MIR, red band, and NDVI of Nbar MODIS product, but these cases were isolated and not always with the same paddock involved. As an example, paddock 15 only showed high correlation between delta height and delta MIR (−0.603) but this satellite variable had very poor correlation values in other paddocks (Table 5).

It is worth considering that in the analyzed period, large variability on weather conditions was observed. During the first three years (2012–2014), weather conditions were relatively favorable, which resulted in NDVI values above or close to the average conditions of a 30 years series, while in April–July 2015, an intense drought period occurred [42]. Hence, the low correlation observed in our research cannot be attributed to a lack of variability in the observed values.

During the analysis process, we sought for possible common field characteristics in paddocks, such as size of the paddocks (Table 1), location (Figure 1), or field data CV (Figure 3 boxplots) with the same response to a specific satellite information signal, but no explanatory co-variable was found.

Considering paddocks 9, 11, 12, and 13 (all paddocks from the same farm) and taking into account characteristics that could be detected by remote sensing, the first two paddocks had relatively homogeneous conditions related to soil types, elevation, vegetation, and historical management, and the other two had very different conditions, being more heterogeneous in relation to soils, elevation, water sources, vegetation, and size. These could be the reasons that field measurements in paddocks 9 and 11 have strong correlation with different satellite variables while paddocks 12 and 13 did not (Table 4). On the other hand, paddock 19, the third paddock with significant correlation values with several satellite variables, had no homogeneous conditions and, therefore, this statement cannot be generalized.

Furthermore, the results of Cimbelli and Vitale [30] suggested that higher grass had a bigger component of the red band, but our results could not be explained by that either. Paddocks with higher values of median height (average or median of sampling dates, and maximum observed value) had different spectral response.

As it was shown, the spatial variability (heterogeneity) observed in native grasslands under grazing conditions is extreme, and this makes it difficult to manage, plan, and characterize at the paddock scale with a single average or even median field measurement value. Considering this, it is even more difficult to try to do so based on earth observation information that provides a value for each pixel, no matter how good the information is.

Additionally, more field information, such as density or vegetation cover, water content, chlorophyll level, or percentage of senescent material, needs to be analyzed and monitored in order to explain differences found between spectral information responses in different paddocks.

Most of the studies, including this one, have used a single sensor to analyze a very complex and heterogeneous ecosystem and this could probably be a limitation. Bearing this in mind, Wachendorf et al. [17] propose developing a system with complementary sensors to overcame these limitations and provide better estimations of different grassland characteristics. In addition to this, the integration of different sources of information (remote sensing, field data, air photos, and street-level imagery) to monitor grasslands, also seems to be an auspicious methodology [43,44]. SAR data (radar remote sensing) calculated from X- or C-band were explored too, with promising results [45,46]. On the other hand, some authors propose hyperspectral and high-resolution images as an option to overcome the difficulties at a paddock scale grasslands monitor [47]. Finally, drones and other unmanned aerial vehicles offer an opportunity for new applications, proving higher spatial resolution and customized spectral and temporal resolution [17,48]. It is worth mentioning that as spatial resolution increases, it is more difficult to scale the analysis to a regional or national level. Moreover, a decision support system needs to be simple to be used by different stakeholders.

5. Conclusions

As it was expected, height of native grasslands is extremely variable within paddocks for each sampling date and between dates (seasonal variability). This variability is what we must deal with when we analyze native grassland forage availability and satellite information, and, at least at these spatial resolutions (500 m, 250 m, and 30 m pixel), the estimation of pasture height variability cannot be represented accurately.

We did not find high correlations between field measurements of height and MODIS composite/daily variable when we analyzed all the paddocks considered together or paddock by paddock. However, some areas of future work seem to be justified. The daily red band of Nbar MODIS product seems to be a promising variable to explore, with relatively good correlation values in 41% of the paddocks. When composite MODIS images were considered, MIR had the best performance with 29% of the paddocks showing negative correlation values higher than 0.45.

This work aims to contribute to manage the grazing process on livestock production systems, based on Earth observation information. Our results showed that no MODIS composite/daily variable was able to predict robustly the native grassland height behavior, but some satellite information came out as promising.

Work is needed in order to find remote sensing methods that can be used to monitor the "instantaneous" condition of grasslands (height or available biomass), and this research has evidenced some of the related difficulties and opportunities.

Author Contributions: Conceptualization, G.T., W.B., and P.C.; methodology, G.T., W.B., and P.C.; formal analysis, G.T.; investigation, A.R. and M.D.C.; writing—original draft preparation, G.T.; writing—review and editing, G.T., W.B., A.R., M.D.C., and P.C.

Funding: This research has been conducted as part of a PhD program (Facultad de Agronomía, Universidad de la República, Uruguay) supported by the Agro-climate and Information System Unit (GRAS) of the National Agricultural Research Institute (INIA Uruguay) and a partial scholarship provided by the National Agency for Research and Innovation (ANII Uruguay).

Acknowledgments: We want to specially thank the National Research Programs of Family Farm Production and Pastures and Forages of INIA (National Institute of Agricultural Research, Uruguay) for their contribution with the field data.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Bilenca, D.; Miñarro, F. *Identificación de Áreas Valiosas de Pastizal en las Pampas y Campos de Argentina, Uruguay y Sur de Brasil*, 1st ed.; Fundación Vida Silvestre Argentina: Buenos Aires, Argentina, 2004; ISBN 950942711X.
2. Suttie, J.M.; Reynolds, S.G.; Batello, C. *Grasslands of the World*; Food and Agriculture Organization: Rome, Italy, 2005; ISBN 9251053375.
3. Allen, V.G.; Batello, C.; Berretta, E.J.; Hodgson, J.; Kothmann, M.; Li, X.; McIvor, J.; Milne, J.; Morris, C.; Peeters, A.; et al. An international terminology for grazing lands and grazing animals. *Grass Forage Sci.* **2011**, *66*, 2–28. [CrossRef]
4. Sala, O.E.; Paruelo, J.M. Ecosystem service in grasslands. In *Nature´s Services: Societal Dependence on Natural Ecosystems*; Daily, G., Ed.; Island Press: Washington, DC, USA, 1995; Volume 92, pp. 237–252, ISBN 9780465022342.
5. O'Mara, F.P. The role of grasslands in food security and climate change. *Ann. Bot.* **2012**, *110*, 1263–1270. [CrossRef] [PubMed]
6. Soriano, A. Temperate subhumid grasslands of South America. In *Ecosyst. WorldTemperate subhumid grasslands*; Coupland, R.T., Ed.; Natural Grasslands.. Elsevier Scientific Publishing Company: Amsterdam, the Netherlands, 1991; Volume 8A, pp. 367–407.
7. Berretta, E.; Risso, D.; Montossi, F.; Pigurina, G. Campos in Uruguay. In *Grassland Ecophysiology and Grazing*, 1st ed.; CABI Publishing: New York, NY, USA, 2000; pp. 377–394.
8. Rosengurtt, B. *Estudios Sobre Praderas Naturales del Uruguay: 3 Contribución*; Casa Barreiro y Ramos: Montevideo, Uruguay, 1943.
9. Altesor, A.; Pezzani, F. Relationship between spatial strategies and morphological attributes in a Uruguayan grassland: A functional approach. *J. Veg. Sci.* **1999**, *10*, 457–462. [CrossRef]
10. Boggiano, P.; Berretta, E. Factores que afectan la biodiversidad del campo natural. *21 Reun. do Grup. Técnico em Forrageiras do Cone Sul Grup. Campos* **2006**, *1*, 93–104.
11. Wheeler, J.L.; Burns, J.C.; Mochrie, R.D.; Gross, H.D. The choice of fixed or variable stocking rates in grazing experiments. *Exp. Agric.* **1973**, *9*, 289–302. [CrossRef]
12. Aiken, G.E. Invited Review: Grazing management options in meeting objectives of grazing experiments12. *Prof. Anim. Sci.* **2016**, *32*, 1–9. [CrossRef]
13. Mott, G.O. Grazing pressure and the measurement of pasture production. In Proceedings of the Grazing Management, 8th International Grasslands Congress, Reading, UK, 11–21 July 1960; pp. 606–611.
14. Sollenberger, L.E.; Moore, J.E.; Allen, V.G.; Pedreira, C.G.S. Reporting forage allowance in grazing experiments. *Crop Sci.* **2005**, *45*, 896–900. [CrossRef]
15. Do Carmo, M.; Sollenberger, L.E.; Carriquiry, M.; Soca, P. Controlling herbage allowance and selection of cow genotype improve cow-calf productivity in Campos grasslands. *Prof. Anim. Sci.* **2018**, *34*, 32–41. [CrossRef]
16. Do Carmo, M.; Cardozo, G.; Ruggia, A.; Soca, P. Prediction of herbage mass in Campos grassland based on herbage height. In Proceedings of the 10th International Symposium on the Nutrition of Herbivoresdvances, Clermont-Ferrand, France, 2–6 September 2018; p. 418.
17. Wachendorf, M.; Fricke, T.; Möckel, T. Remote sensing as a tool to assess botanical composition, structure, quantity and quality of temperate grasslands. *Grass Forage Sci.* **2017**, *73*, 1–14. [CrossRef]
18. Lawley, V.; Lewis, M.; Clarke, K.; Ostendorf, B. Site-based and remote sensing methods for monitoring indicators of vegetation condition: An Australian review. *Ecol. Indic.* **2016**, *60*, 1273–1283. [CrossRef]
19. Baeza, S.; Lezama, F. Spatial variability of above-ground net primary production in Uruguayan grasslands: A remote sensing approach. *Appl. Veg.* **2010**, *13*, 72–85. [CrossRef]
20. Baldassini, P.; Volante, J.N.J.N.; Califano, L.M.; Paurelo, J.M. Caracterización regional de la estructura y de la productividad de la vegetación de la Puna mediante el uso de imágenes MODIS. *Ecol. Austral* **2012**, *22*, 22–32.
21. Guerschman, J.P.; Paruelo, J.M.; Di Bella, C.; Giallorenzi, M.C.; Pacin, F. Land cover classification in the Argentine Pampas using multi-temporal Landsat TM data. *Int. J. Remote Sens.* **2003**, *24*, 3381–3402. [CrossRef]
22. Piñeiro, G.; Oesterheld, M.; Paruelo, J.M. Seasonal Variation in Aboveground Production and Radiation-use Efficiency of Temperate rangelands Estimated through Remote Sensing. *Ecosystems* **2006**, *9*, 357–373. [CrossRef]

23. An, N.; Price, K.P.; Blair, J.M. Estimating above-ground net primary productivity of the tallgrass prairie ecosystem of the Central Great Plains using AVHRR NDVI. *Int. J. Remote Sens.* **2013**, *34*, 3717–3735. [CrossRef]
24. Li, F.; Zeng, Y.; Luo, J.; Ma, R.; Wu, B. Modeling grassland aboveground biomass using a pure vegetation index. *Ecol. Indic.* **2016**, *62*, 279–288. [CrossRef]
25. Jia, W.; Liu, M.; Yang, Y.; He, H.; Zhu, X.; Yang, F.; Yin, C.; Xiang, W. Estimation and uncertainty analyses of grassland biomass in Northern China: Comparison of multiple remote sensing data sources and modeling approaches. *Ecol. Indic.* **2016**, *60*, 1031–1040. [CrossRef]
26. Olsen, J.L.; Miehe, S.; Ceccato, P.; Fensholt, R. Does EO NDVI seasonal metrics capture variations in species composition and biomass due to grazing in semi-arid grassland savannas? *Biogeosciences* **2015**, *12*, 4407–4419. [CrossRef]
27. Gaitán, J.J.; Bran, D.; Oliva, G.; Ciari, G.; Nakamatsu, V.; Salomone, J.; Ferrante, D.; Buono, G.; Massara, V.; Humano, G.; et al. Evaluating the performance of multiple remote sensing indices to predict the spatial variability of ecosystem structure and functioning in Patagonian steppes. *Ecol. Indic.* **2013**, *34*, 181–191. [CrossRef]
28. Marsett, R.R.C.R.; Qi, J.; Heilman, P.; Biedenbender, S.H.; Watson, M.C.; Amer, S.; Weltz, M.; Goodrich, D.; Marsett, R.R.C.R. Remote Sensing for Grassland Management in the Arid Southwest. *Rangel. Ecol. Manag.* **2006**, *59*, 530–540. [CrossRef]
29. Ali, I.; Cawkwell, F.; Dwyer, E.; Barrett, B.; Green, S. Satellite remote sensing of grasslands: From observation to management. *J. Plant Ecol.* **2016**, *9*, 649–671. [CrossRef]
30. Cimbelli, A.; Vitale, V. Grassland Height Assessment by Satellite Images. *Adv. Remote Sens.* **2017**, *6*, 40–53. [CrossRef]
31. Crabbe, R.A.; Lamb, D.W. *Estimating Biophysical Variables of Pasture Cover Using Sentinel-1 Data*; Precision Agriculture NZ Inc.: Christchurch, New Zealand, 2017; pp. 1–8.
32. Crabbe, R.A.; Lamb, D.W.; Edwards, C.; Andersson, K.; Schneider, D. A Preliminary Investigation of the Potential of Sentinel-1 Radar to Estimate Pasture Biomass in a Grazed, Native Pasture Landscape. *Remote Sens.* **2019**, *11*, 872. [CrossRef]
33. Haydock, K.P.; Shaw, N.H. The comparitive yield method for estimating dry matter yield of pasture. *Aust. J. Exp. Agric.* **1975**, *15*, 663–670.
34. Duveiller, G.; Defourny, P. A conceptual framework to de fi ne the spatial resolution requirements for agricultural monitoring using remote sensing. *Remote Sens. Environ.* **2010**, *114*, 2637–2650. [CrossRef]
35. Didan, K. MOD13Q1 MODIS/Terra Vegetation Indices 16-Day L3 Global 250m SIN Grid V006 [Data Set]. 2015. Available online: https://search.earthdata.nasa.gov/search (accessed on 1 October 2017).
36. Myneni, R.; Knyazikhin, Y.; Park, T. MCD15A3H MODIS/Terra+Aqua Leaf Area Index/FPAR 4-day L4 Global 500 m SIN Grid V006 [Data Set]. 2015. Available online: https://search.earthdata.nasa.gov/search (accessed on 1 October 2017).
37. Vermote, E.F.; Roger, J.C.; Ray, J.P. MODIS Surface Reflectance User's Guide collection 6. *MODIS L. Surf. Reflectance Sci. Comput. Facil* **2015**, 1–36.
38. Schaaf, C.; Wang, Z. MCD43A4 MODIS/Terra+Aqua BRDF/Albedo Nadir BRDF Adjusted Ref Daily L3 Global-500m V006 [Data Set]. NASA EOSDIS Land Processes DAAC. 2015. Available online: https://search.earthdata.nasa.gov/search (accessed on 1 October 2017).
39. The United States Geological Survey. *Product Guide LANDSAT 8 Surface Reflectance Code (LASRC) Product*; Version 2.0; EROS: Sioux Falls, SD, USA, 2018.
40. Laca, E.A.; Demment, M.W.; Winckel, J.; Kie, J.G. Comparison of weight estimate and rising-plate meter methods to measure herbage mass of a mountain meadow. *J. Range Manag.* **1989**, *42*, 71–75. [CrossRef]
41. Payero, J.O.; Neale, C.M.U.; Wright, J.L. Comparision of eleven vegetation indices for estimating plant height of alfalfa and grass. *Appl. Eng. Agric.* **2004**, *20*, 385–394. [CrossRef]
42. INIA (GRAS) NDVI Nacional Monitoring. Available online: http://www.inia.uy/gras/Monitoreo-Ambiental/Monitoreo-de-la-vegetación (accessed on 1 April 2019).
43. d'Andrimont, R.; Lemoine, G.; Velde, M. Targeted Grassland Monitoring at Parcel Level Using Sentinels, Street-Level Images and Field Observations. *Remote Sens.* **2018**, *10*, 1300. [CrossRef]
44. Wood, E.M.; Pidgeon, A.M.; Radeloff, V.C.; Keuler, N.S. Image texture as a remotely sensed measure of vegetation structure. *Remote Sens. Environ.* **2012**, *121*, 516–526. [CrossRef]

45. Zalite, K. *Radar Remote Sensing for Monitoring Forest Floods and Agricultural Grasslands*; University of Tartu Press: Tartu, Estonia, 2016; ISBN 978-9949-77-025-0.
46. Tamm, T.; Zalite, K.; Voormansik, K.; Talgre, L. Relating Sentinel-1 Interferometric Coherence to Mowing Events on Grasslands. *Remote Sens.* **2016**, *8*, 802. [CrossRef]
47. López-Díaz, J.E.; González-Rodríguez, A. Measuring Herbage Mass by Non-Destructive Methods: A Review. *J. Agric. Sci. Technol.* **2011**, *1*, 303–314.
48. Grüner, E.; Astor, T.; Wachendorf, M. Biomass Prediction of Heterogeneous Temperate Grasslands Using an SfM Approach Based on UAV Imaging. *Agronomy* **2019**, *9*, 54. [CrossRef]