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Space-time quantification of aboveground net primary productivity service supply capacity in high Andean bofedales using remote sensors

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Abstract: The aboveground net primary productivity (*ANPP*) of bofedales is one of the most important indicators for the provision of ecosystem services in the high Andean areas. In the case of bofedales, the evaluation of the *ANPP* supply capacity as a service on a spatial and temporal scale through remote sensing has been little addressed. The capacity, intra and interannual, to provide the *ANPP* of the high Andean wetlands was quantified at a spatial and temporal level through remote sensing. The normalized difference vegetation index (*NDVI*) of the MODIS sensor was used according to the Monteith model (1972), product of the incident photosynthetically active radiation, fraction of the absorbed radiation, and the efficiency of using the radiation of the calibrated vegetation with dry matter sampling in the field. Results show an *ANPP* prediction R^2 of 0.52 ($p < 0.05$), with no significant spatial difference between field samples. When applying the model, the intra-annual temporary *ANPP* supply capacity presents a maximum average of 160.54 kg DM·ha^{-1}·month^{-1} in the rainy season (December–May) and a maximum average of 81.17 kg DM·ha^{-1}·month^{-1} in the dry season (June–October). In 2003–2020, the interannual temporary capacity presented values of 1100–1700 kg DM·ha^{-1}·year^{-1}. This makes it possible not to affect the sustainability of the wetlands and prevent their depletion and degradation. Understanding the *ANPP* supply capacity of bofedales can favour the efficient use of the resource and indirectly benefit its conservation.

Keywords: aboveground net primary productivity (*ANPP*), bofedales, ecosystem services, high Andean wetlands, MODIS, Monteith model, productivity, remote sensing, supply capacity

INTRODUCTION

Bofedales, or tropical high Andean wetlands, are ecosystems of hydromorphic origin, which are generally distributed in valley bottoms and plateaus of the Andes above 3500 m a.s.l. These ecosystems are supplied by rainfall and glacial melting, with a dominance of hydrophilic perennial vegetation and peat accumulation [Chimner *et al.* 2020; Maldonado Fonkén 2014]. The bofedales provide multiple ecosystem services, which include regulation of water flow, carbon sequestration, maintenance of biodiversity, food for livestock, among others [Franco Vidal *et al.* 2013]. Their main uses by local communities are animal grazing and peat extraction [Yaranga 2020], which involve the use of aboveground net primary productivity (*ANPP*). The wetlands are considered to be some of the most productive ecosystems [Faccio 2010]. However, in recent years, the anthropogenic pressure on these ecosystems has increased due to multiple factors, such as overgrazing [Cochi-Machaca *et al.* 2018], uncontrolled peat extraction for energy purposes [Caro *et al.* 2014], change of land use for crops [Yaranga *et al.* 2019] and climate change that modifies precipitation and temperature regimes [Anderson *et al.* 2021]. In the long term, this could result in drying and decay of bofedales that are not hydrologically connected to lakes and glaciers [Baiker 2020].

The *ANPP* is the accumulation of aerial plant biomass produced by different plant communities in a given time [Oesterheld *et al.* 2014]. This fundamental ecological variable is important, not only because it measures energy input and terrestrial carbon dioxide assimilation, but also because of its importance as an indicator of the state of health and stability of an ecosystem [Tao *et al.* 2003]. Traditionally, this was studied using biometric techniques based on the incremental measurement of aerial biomass dry matter, i.e. cutting and weighing. However, these techniques have been used in small-scale observations, making it difficult to extrapolate their estimation to a large scale due to a poor monitoring network [Lu 2006]. The development of remote sensing techniques for ecosystems provides tools for estimating the *ANPP* at different spatial and temporal levels [Lees *et al.* 2018], which can replace or complement traditional monitoring methods, even at a regional scale, under an efficient and low-cost approach [Running *et al.* 2000].

Techniques based on remote sensing allow to study wetlands at different spatial and temporal scales of variables, such as vegetation distribution, transpiration, and photosynthetic activity to monitor the dynamics of the *ANPP* as an indicator of health status, and capacity in terms of productivity [Tao *et al.* 2003]. Using the Monteith model (1972), it is possible to obtain the information explicitly and with considerable savings in time and resources [Lees *et al.* 2019], compared to the traditional biomass collection method [Guido *et al.* 2014]. The Monteith model (1972) defines the *ANPP* as the product of incident photosynthetically active radiation (*PAR*), fraction of absorbed photosynthetically active radiation (f*PAR*), and the radiation use efficiency (*RUE*). The *PAR* is derived from daily available radiation meteorological data sources; f*PAR* is found through models used by Grigera *et al.* [2007] which is based on the normalized difference vegetation index (*NDVI*). The *RUE* is obtained through a linear model between absorbed photosynthetically active radiation (*APAR*), a product of *PAR* and f*PAR*, and continuous field monitoring data for a given period [Baeza *et al.* 2011; Oyarzabal *et al.* 2010; Verón *et al.* 2005].

The monitoring and quantification of the *ANPP* as an indicator is essential to evaluate the functioning of ecosystems, as it is the starting point of the food chain flow and for the supply of other ecosystem services for the benefit of human [Irisarri *et al.* 2013]. The capacity to provide ecosystem services is defined as the maximum amount of ecosystem services providede without affecting its future sustainability. It can be quantified and evaluated in biophysical terms [Burkhard *et al.* 2009; Hein *et al.* 2016; Martín-López *et al.* 2007]. Therefore, the importance of evaluating the capacity of bofedales to provide *ANPP* supply services lies in their ability to cover the demand for the intensity of use (e.g. grazing, peat extraction) without a negative impact on the sustainability of these ecosystems, so as not to affect depletion and/or degradation that may influence other ecosystem services in the future [Costanza *et al.* 2007]. Some experiences in evaluating the service provision capacity of the *ANPP* through the use of remote sensing can be seen in Caride *et al.* [2012], Moreau *et al.* [2003], and Vargas *et al.* [2019].

The study of the *ANPP* supply capacity of the bofedales to maintain the flow of the provisioning service on a spatial and temporal scale through remote sensing has been little addressed, focusing mainly on botanical and phytoecological studies, quite localised and in a determined time, generating little information in this regard [Chávez *et al.* 2019; Chimner *et al.* 2019, Moreau *et al.* 2003; Paruelo *et al.* 2000; Yaranga 2020]. Therefore, this study aims to quantify at the spatio-temporal level the capacity, intra and inter-annual, of the *ANPP* supply service of the high Andean wetlands, based on the model of Monteith (1972) using remote sensing.

MATERIALS AND METHODS

STUDY AREA

The study area comprises three bofedales established as monitoring points (stations), E1 (11,952°S, 75,046°W, 4546 m a.s.l.); E2 (11,954°S, 75,048°W, 4522 m a.s.l.); E3 (11,963°S and 75,051°W, 4402 m a.s.l.). They are located at the head of the Shullcas River sub-basin, a short distance from the Huaytapallana mountain in the Junin Region, Peru (Fig. 1). The climate is very humid and frigid. The surrounding landscape is mountainous with very rugged topography. In this area, high Andean grasslands are the predominant vegetation. The bofedales present a heterogeneous distribution with stable patches in locations of constant underground outcrop water. These locations are mostly used for livestock production, notably sheep and South American camelids (alpacas and llamas).

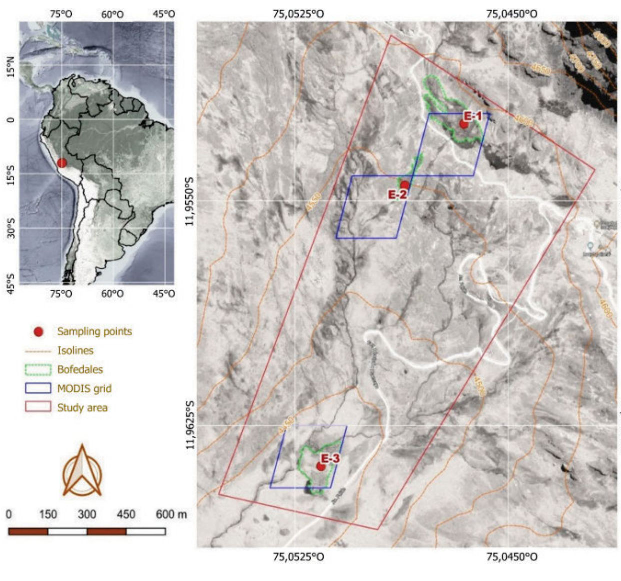

Fig. 1. Location of bofedales in the Shullcas River sub-basin; the blue polygons correspond to the 250 × 250 m MODIS pixels; source: own elaboration

SAMPLING AND DETERMINATION OF NET AERIAL PRIMARY PRODUCTION IN THE FIELD

Data collection in the field was carried out by sampling at the three stations using the radial transept method (Fig. 2a), where three 30-meter lines were set and then 10 quadrants of 1 m^2 were arranged, with a separation of 10 m according to the recommendation of the USDA – Forest Service [Siguayro 2008].

To calculate biomass (dry matter per 0.25 m^2), quadrants of one square meter were divided into four equal parts of 0.5 × 0.5 m. The four squares were assigned regular cutting periods every 30, 60, 90, and 120 days. The cut was made one centimetre above the ground for 12 months (March 2018 to February 2019) every 30 days. The biomass collected from each square was deposited in polyethylene bags, which were correctly labelled indicating the cutting period, origin, and the number of the quadrant. They were then transferred to the animal nutrition laboratory of the Facultad de Zootecnia of the Universidad Nacional del Centro del Perú in Huancayo (Junin Region), where they were weighed on a digital scale and dried in an oven at 65°C for 48 h. The samples were weighed before and after drying to evaluate the moisture and dry matter content. In total, 30 census units (10 units per bofedal) belonging to three different bofedales were sampled monthly for 12 months, making a total of 360 samples.

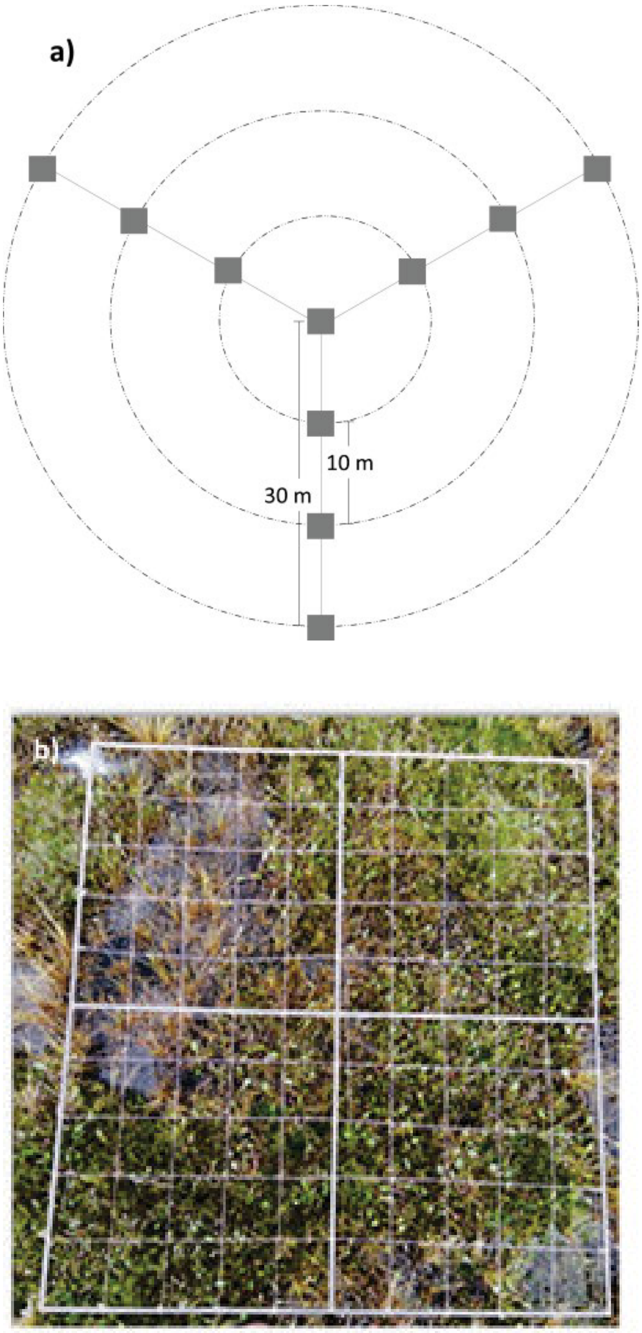

Fig. 2. Monitoring points: a) radial linear transept design used in the distribution of the control plots according to Siguayro [2008], b) square with 100 divisions of 10 × 10 cm in the quadrant of a square meter; source: own elaboration

The *ANPP* was determined by the difference in dry matter (*DM*, in g·(0.25 $m^2)^{-1}$·$month^{-1}$, is the measure of dry matter in grams per 0.25 square meters of the month divided by the time elapsed between sampling) obtained in the month analysed and the previous month [Sala, Austin 2000], as shown in Equation (1):

$$ANPP_{0.25} = (DM_{ta} \cdot 0.25 - DM_{t-1} \cdot 0.25)/30 \qquad (1)$$

where: $ANPP_{0.25}$ = aboveground net primary productivity from 0.25 m^2 (g) every 30 days, DM_{ta} = dry mass in the analysed month (g), 0.25 = area of analysed square (equal of 0.25 m^2), DM_{t-1} = dry mass in the previous month (g), 30 = time elapsed between sampling (equal of 30 days).

By default, the *ANPP* for the month of March was cancelled to obtain the productivity of the following month. This allowed to obtain 330 *ANPP* values.

COLLECTION AND PROCESSING OF DATA FROM REMOTE SENSORS

The remote sensing data used was the normalized difference vegetation index (*NDVI*) derived from the MOD13Q1 product of the MODIS (Moderate Resolution Imaging Spectroradiometer) sensor located on the EOS Terra and EOS Aqua satellites, for 11 months from April 2018 until February 2019. The images have a temporal resolution of 16 days and a spatial resolution of 250 × 250 m, available on the following website: https://modis.ornl.gov/globalsubset/. The monthly average of the *NDVI* for the three pixels that covered all the wetlands during the mentioned period was used.

Daily data of incident radiation or photosynthetically active radiation (*PAR*, in MJ·m^{-2}·day^{-1}) was obtained from the POWER database (Prediction of Worldwide Energy Resource), a project of the National Aeronautics and Space Administration (NASA) specialised in radiation data for renewable energies, sustainable constructions and agroclimatology, available on the following website: https://power.larc.nasa.gov/data-access-viewer/. These data were multiplied by 0.48, the estimated amount of radiation that can reach the land surface [McCree 1972].

The *ANPP* (g DM·m^{-2}·$month^{-1}$) for the wetlands was determined using the Monteith model (1972), a model that considers the incident photosynthetically active radiation (*PAR*, in MJ·m^{-2}·$month^{-1}$), fraction of absorbed photosynthetically active radiation (f*PAR*), and the efficiency in the use of radiation (*RUE*, in g DM·MJ^{-1}), see Equation (2). For more details of the model, see Figure 3.

$$ANPP = PAR \cdot \mathrm{f}PAR \cdot RUE \qquad (2)$$

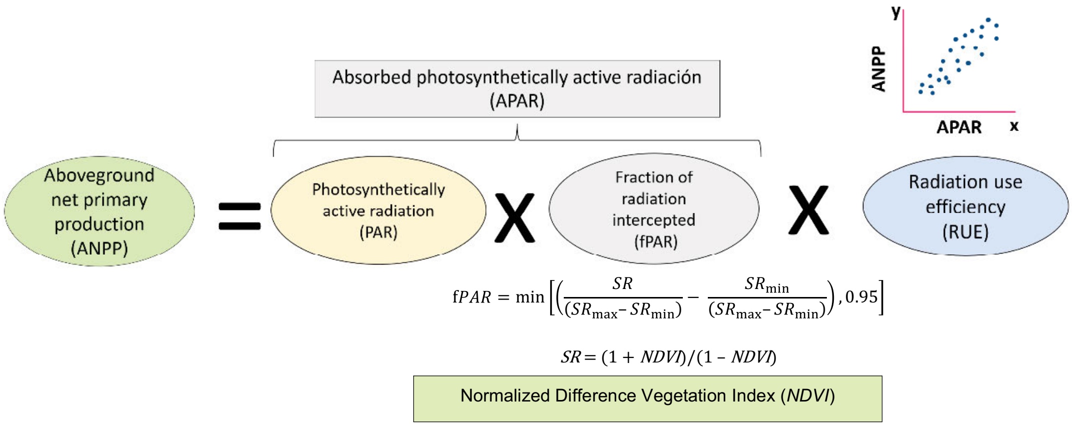

Fig. 3. Details of the Monteith model (1972), applied to determine the *ANPP* of high Andean wetlands; source: own elaboration based on the diagram OYARZABAL *et al.* [2010]

The *PAR* is related to the photosynthetic processes in plants, found in the electromagnetic spectrum (400–700 nm), and it is related to the hours of sunlight that reaches the land surface (heliophile daily values); 48% of the value of the incident solar radiation that effectively reaches the land surface was considered [MCCREE 1972].

The f*PAR* was calculated taking into account the model generated by GRIGERA *et al.* [2007] from the normalized difference vegetation index (*NDVI*) using the simple ratio (*SR*), which showed a good linear correlation with the leaf area index (*LAI*).

$$SR = (1 + NDVI)/(1 - NDVI) \tag{3}$$

The *NDVI* and f*PAR* relationship were parameterised with minimum and maximum values of the *NDVI* (SR_{min} = 2.48, SR_{max} = 4.25). It is considered that f*PAR* = 0 when *NDVI* values apply to covers with bare or senescent soil, while the maximum value is f*PAR* = 0.95 corresponding to values with a high *NDVI* and a large amount of green biomass [GRIGERA *et al.* 2007].

$$fPAR = \min\left[\left(\frac{SR}{(SR_{max} - SR_{min})} - \frac{SR_{min}}{(SR_{max} - SR_{min})}\right), 0.95\right] \tag{4}$$

Absorbed photosynthetically active radiation (*APAR*) arose from the result of multiplying *PAR*·f*PAR* [OYARZABAL *et al.* 2010]. A linear relationship was generated for each station between the *APAR* and the *ANPP* field results.

To estimate the radiation use efficiency (*RUE*), an approximation was used by means of a simple linear contrast model between data of the aboveground net primary productivity (*ANPP*) taken in the field and the values found of the absorbed photosynthetically active radiation (*APAR*). This approach has some advantages; it is very versatile in case one wants to find variation between months, seasons, or years [OYARZABAL *et al.* 2010].

ANALYSIS OF DATA

The spatial statistical analysis was performed through an analysis of variance (ANOVA) to verify the differences in the means of the three sampling stations. Likewise, a simple linear regression analysis was carried out, having the *ANPP* as the variable to be predicted and the *APAR* as the predictor variable. The assumptions of normality, which served for validation, were applied to the residual of the regression using the Shapiro–Wilk normality test, as well as the double root transformation of both variables to improve the fit of the model. A monthly temporal analysis was also carried out during the sampling period for average values of f*PAR*, *APAR*, and *ANPP*, to analyse seasonal behaviour. All analyses were performed with Excel, R studio, and Statgraphics software.

Once the model was validated, the intra-annual (monthly) temporal analysis of the *ANPP* was carried out for the entire evaluation period and all stations. For this, the values from each station and each interval of 16 days were averaged during the period of 2003–2020 (period of availability of complete data from the MODIS sensor). The analysis of the coefficient of variation (*CV*, %) was carried out to observe the dispersion of data in all the months.

The interannual (annual) temporal variability of the *ANPP* was carried out through annual means of the three seasons and it was complemented with the percentage of variation coefficient to observe the dispersion of data. The Mann–Kendall test was used to evaluate the trends of the three stations during the period of 2003–2020.

RESULTS

SPATIAL ASSESSMENT

The results found for the dry matter difference obtained between the month analysed and the previous month had values less than zero. If this was the case, the absence of productivity was considered. Zero *ANPP* reduced the set of valid data to 158. All these data obtained were averaged monthly for each sampling station, reaching 30 averaged data.

In the spatial analysis, the results, both from the field (*ANPP*) and those from remote sensors (f*PAR*, *APAR*), have a seasonal and synchronised behaviour throughout the months evaluated. They present higher values with a lot of spatial variability in the rainy season (September–March) and lower values with low variability in the dry season (April–August). Thus, they express marked differences in each season, characteristic for Andean latitudes (Fig. 4). Likewise, the biomass cuts carried out monthly presented average values of the maximum aboveground net primary productivity (*ANPP*) of

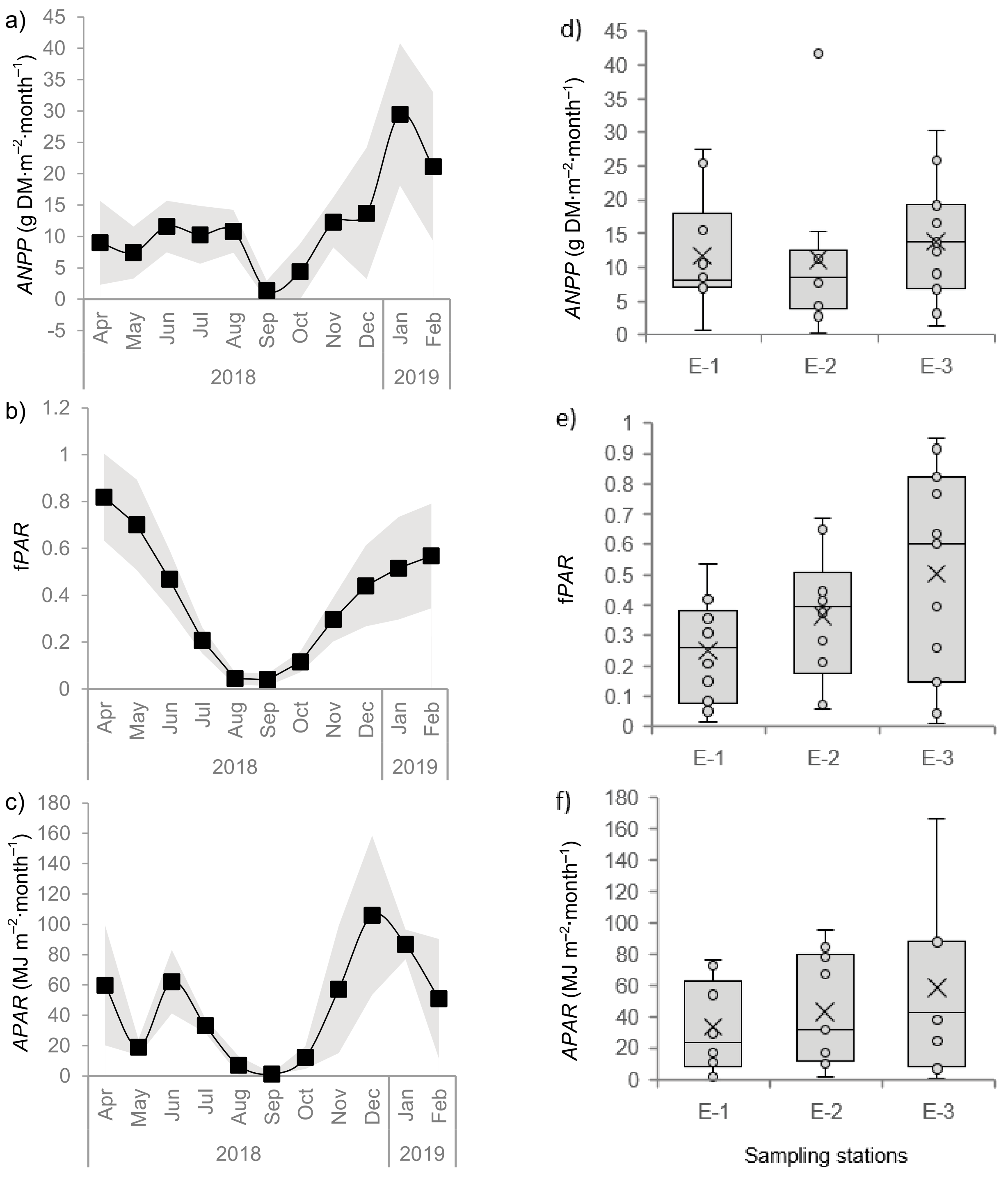

Fig. 4. Spatial distribution: a) average aboveground net primary productivity (*ANPP*) for each month originating from the cuts made in the field, b) average fraction of absorbed photosynthetically active radiation (f*PAR*) for the months evaluated from the normalized difference vegetation index (*NDVI*) values and the model of GRIGERA *et al.* [2007], c) average absorbed photosynthetically active radiation (*APAR*), originates from the product of Incident photosynthetically active radiation (*PAR*) and f*PAR*, d) box plot of the distribution of average *ANPP* obtained in the field by harvesting biomass from the three stations, e) box plot of average f*PAR* distribution obtained from *NDVI* values, f) box plot of the *APAR* for the three stations based on satellite and meteorological information; the lead-coloured spaces correspond to the standard deviation, boxes constitute the interquartile range, bars represent the maximum and minimum values, and the central line identifies the average value; source: own study

29.46 g DM·m^{-2}·month^{-1} in January 2019, and minimum averages of 1.40 g DM·m^{-2}·month^{-1} September 2018 (Fig. 4a). In the inter-station evaluation through the analysis (ANOVA) of the average *ANPP* during the entire sampling period, the differences were not significant (p > 0.05); the average values were 11.71, 11.17, and 13.87 g DM·m^{-2}·month^{-1} in stations 1, 2 and 3, respectively (Fig. 4d). Likewise, E-3 showed greater variability and E-2 minimal variability. The latter present an atypical average that we consider important in the study because it is a logical increase in rainy seasons.

The fraction of absorbed photosynthetically active radiation (f*PAR*) presented an average maximum value of 0.81 in April and an average minimum value of 0.04 in September, with greater spatial variability in rainy months and less in dry months (Fig. 4b). The mean differences were not significant between the sampling stations ($p > 0.05$), but they did show greater dispersion in E-3 and less dispersion in E-1 (Fig. 4e).

The *APAR* presented a maximum value of 105.96 $MJ \cdot m^{-2} \cdot month^{-1}$ in December 2019, and a minimum average of 1.25 $MJ \cdot m^{-2} \cdot month^{-1}$ in September 2018 (Fig. 4c). Likewise, E-1 has a mean of 33.65 $MJ \cdot m^{-2} \cdot month^{-1}$, with the mean and variability being the lowest; not so far away and with a similar mean, E-2 has a mean of 43.03 $MJ \cdot m^{-2} \cdot month^{-1}$; and station E-3 show the highest mean and greater variability, with 58.71 $MJ \cdot m^{-2} \cdot month^{-1}$, without statistical differences between them ($p > 0.05$) – Figure 4f.

CALIBRATION OF THE MONTEITH MODEL

The spatial model of the linear relationship between the *ANPP* as the variable to be predicted and the *APAR* as the predictor variable shows positive linearity, where the *APAR* explains 52% of the *ANPP* of the variation in the total data set ($ANPP = \left(0.257 + 0.056\sqrt{APAR}\right)^2$); $R^2 = 0.52$; $n = 30$; $p < 0.05$). This allowed to determine $RUE = 0.056$ g $DM \cdot MJ^{-1}$, defined as the slope of the linear model (Fig. 5). The residuals of this model showed evidence of a normal distribution ($p > 0.05$) and with acceptance of the assumption of homoscedasticity with constant variation along the line. Details and contributions to the model for each station are shown in Table 1, including means of *ANPP* and *APAR*, and regressions together with the coefficient of determination (R^2). It can be seen that the best fits are obtained with E-2 ($R^2 = 0.67$) and E-3 ($R^2 = 0.57$), while the worst fit is obtained with E-1 ($R^2 = 0.37$).

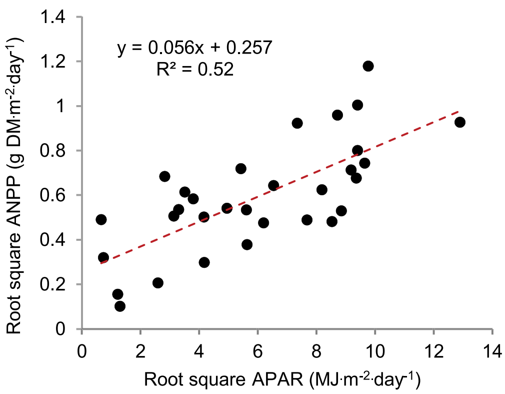

Fig. 5. The relationship between the average aboveground net primary productivity (*ANPP*) for the three stations derived from monthly biomass cuts in the field and the absorbed photosynthetically active radiation (*APAR*), from the normalized difference vegetation index (*NDVI*), and the incident photosynthetically active radiation (*PAR*) obtained from remote sensing; source: own study

TEMPORAL ASSESSMENT AND APPLICATION OF THE MODEL

The evaluation and availability of historical data provided by remote sensing (f*PAR* and *APAR*) and the application of the Monteith model to quantify *ANPP* carried out and analysed in this study, allowed to estimate the capacity to supply the *ANPP* of bofedales on a time scale in the 2003–2020 period. These presented a sustained variability with capacity ranging from 1100 to 1700 kg $DM \cdot ha^{-1} \cdot y^{-1}$ approximately in the three sampling stations, with E-3 being the most productive. The trend throughout the years evaluated was slightly positive, although not significant in the Mann–Kendall test ($p > 0.05$). The maximum production was obtained in 2016 (E-1 = 1140, E-2 = 1640.07 and E-3 = 1700.89 kg $DM \cdot ha^{-1} \cdot y^{-1}$) and the least productive was 2012 (E-1 = 1117.45, E-2 = 1330.68 and E-3 = 1499.80 kg $DM \cdot ha^{-1} \cdot y^{-1}$) – Figure 6a. The interannual temporal variability of the *ANPP* (Fig. 6b), evaluated with the coefficient of variation, maintains a sustained variability over time, with a minimum variability of 34% at E-2 in 2016 up to a maximum variability of 49% at E-1 in 2013. The years with the least variability between sampling stations are 2005 and 2015, in which it is observed that the coefficient of variation values are similar.

The quantification of the monthly *ANPP* capacity of the bofedales presents a bimodal distribution throughout the months (Fig. 6c), the first and most pronounced is between April, May, and June (maximum cumulative average *ANPP* for May, E-3 = 160.54 kg $DM \cdot ha^{-1} \cdot y^{-1}$), and the second in November and January (*ANPP* maximum accumulated average of November, E-3 = 143.22 kg $DM \cdot ha^{-1} \cdot y^{-1}$). The lowest maximum average production was in October at E-1 = 81.17 kg $DM \cdot ha^{-1} \cdot y^{-1}$. These results agree with the end and beginning of the rainy season in the Andean latitudes. The greatest intra-annual temporal variability of the *ANPP* (Fig. 6d) is in December, January, February, and March, the latter being the greatest of all. The E-1 presents greater variability with the maximum variation of 64.84%; this corresponds to the months with more cloudiness in the images, and so

Table 1. Detail of linear regression and the coefficient of determination (R^2) between *ANPP* and *APAR* for the three stations

Station	Mean *ANPP* g $DM \cdot m^{-2} \cdot day^{-1}$	Mean *APAR* $MJ \cdot m^{-2} \cdot month^{-1}$	Regression	R^2 *ANPP – APAR*
E-1	0.39 ±0.29 a	33.65 ±29.28 a	$y = \left(0.332 + 0.049\sqrt{x}\right)^2$	0.37
E-2	0.37 ±0.39 a	43.03 ±34.90 a	$y = \left(0.117 + 0.072\sqrt{x}\right)^2$	0.57
E-3	0.46 ±0.30 a	58.71 ±50.90 a	$y = \left(0.279 + 0.053\sqrt{x}\right)^2$	0.67

Explanation: a = mean values with the same letter do not differ significantly ($p > 0.05$).
Source: own study.

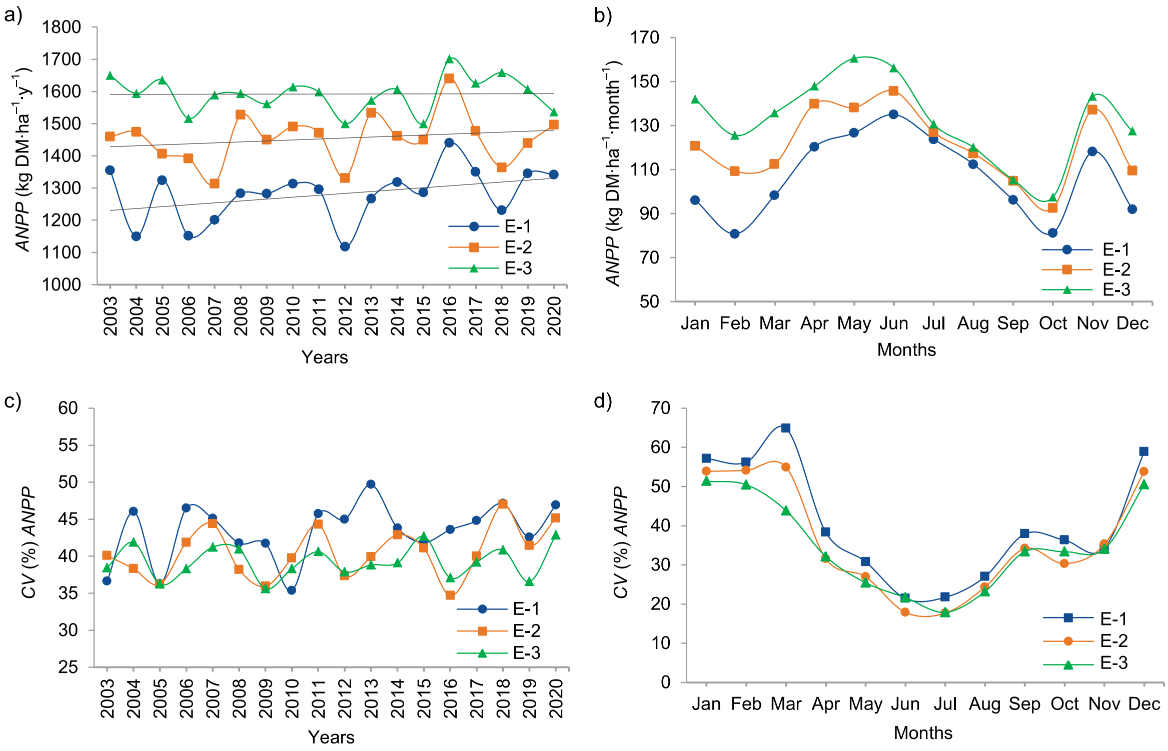

Fig. 6. Temporal distribution: a) accumulated interannual temporal aboveground net primary productivity (*ANPP*) in 2003–2020 with the Monteith model and the three stations, based remote sensors (dotted lines show Mann–Kendall's test for trend, $p > 0.05$), b) accumulated intra-annual temporal *ANPP* (January–December) at the three sampling stations with the application of the Monteith model, based on remote sensors, c) interannual temporal variability (2003–2020) of the *ANPP*, d) intra-annual temporal variability (January–December) of the monthly *ANPP* provided; c) and d) both indicated as the coefficient of variation (*CV*); source: own study

they do not have the desired quality. Very different are the variations in May, June, July, and August (E-1 = 21.73%, E-2 = 17.69% and E-3 = 17.88%) with low variability and higher quality images.

DISCUSSION

The acceleration of the vegetation growth with higher productivity was in the rainy months (December–May), because of a high photosynthetic rate and the increase in f*PAR* and *APAR* values due to the effects of the spring prelude (September, October, and November), where the highest levels of radiation and the beginning of rains are reported. On the contrary, in the dry season (May–August) the increase in senescent material is accentuated, associated with the decrease in the efficient use of radiation, due to the change in the regime of effective precipitation and considerable changes in temperature during the day and at night. This behaviour recorded by remote sensors contrasts a lot with the studies carried out by Baeza *et al.* [2010], Oyarzabal *et al.* [2010], Pezzani *et al.* [2011], Baldassini *et al.* [2012], and Guido *et al.* [2014] as they report an increase in f*PAR* and *APAR*. These are consistent with the high levels of radiation and the prelude to rains, as well as reduced levels in months where precipitation decreases. The variability in these results is mainly due to the high presence of clouds (as shown in images) during rainy seasons, which alters the results with extreme values, often erroneous, and sometimes limits remote sensing studies at these latitudes.

The average *ANPP* found in the field is well below that found by Buttolph and Coppock [2004] with an average of 60 g DM·m^{-2}·month^{-1} in wetlands on the western edge of the Altiplano in Bolivia and below 49 g DM·m^{-2}·month^{-1} on average found by Buono *et al.* [2010] in the humid Patagonian mallines. These differences may be due to extreme climatic factors that affect the development of vegetation, such as temperature, night frosts, periods of abrupt and constant freezing and thawing, in addition to the marked seasonality of rainfall, leaving long periods of low water [Buttolph, Coppock 2004]. Furthermore, these factors have a direct effect on the diversity, composition, and floristic distribution, where each species has a greater or lesser capacity to adapt to the risk of frost, and they are even different in the efficient use of radiation and water retention [Castellaro *et al.* 1998; Yaranga 2020]. Likewise, it can vary according to limiting factors, such as soil pH, livestock management, physiography, orography, soil type, and texture, etc. [Baldassini *et al.* 2012].

The calibration and contrast of data from the remote sensors against the field data allowed for the application of the Monteith model. It was quite efficient and consistent with the estimation of the *ANPP* for the high Andean wetlands. The model presents an acceptable correlation, similar to that found by Moreau *et al.* [2003], Baeza *et al.* [2011], and Irisarri *et al.* [2012], with R^2 equal to 0.58, 0.67, and 0.64 respectively. These results show great representativeness, despite circumstances and diversity of factors that could affect them, such as the presence of clouds, sampling error, the percentage of the pixel that covers the bofedal, temperature, precipitation, terrain slope, the productivity of each species, the size of the wetland patch, among others [Buttolph, Coppock 2004].

The temporal variability of the estimated *ANPP* for the wetlands is due to a seasonal dynamic sustained over time with a non-significant positive trend. What was found contrasts with research by Washington-Allen *et al.* [2008], Chavez *et al.* [2019] and Anderson *et al.* [2021] who used *NDVI* data to estimate productivity over long periods, obtaining acceptable approximations of the dynamics, with positive trend, at different latitudes of the bofedales in northern Chile and bofedales of the northern Bolivian highlands. There, factors, such as temperature and precipitation, determine the development of vegetation in the wetlands [Mazzarino, Finn 2016]. However, many evaluations of the temporal variability of *ANPP* and biomass of bofedales with remote sensors were based on climatic data, such as precipitation and temperature, in contrast to the *NDVI*. This correlation being still not so clear, and may be due to the lag between precipitation, temperature and the gradual development of vegetation in the face of seasonal changes [Durante *et al.* 2017; Pauca-Tanco *et al.* 2020]. This disadvantage could be resolved with the results obtained in this study as they contribute to the precision in the estimation of the *ANPP* over time, since the Monteith model (1972) works without a seasonal lag, applying photosynthetic physiological criteria to vegetation, in contrast to the capacity and efficiency of capturing and transforming radiation or solar energy into chemical energy used by plants for their productivity.

The *ANPP* values found by remote sensing are the maximum capacity of the high Andean wetlands studied for supply as an ecosystem service on a temporal and spatial scale. This information, on the one hand, shows the supply of ecosystem services and, on the other, helps to analyse the sustainability of these Andean ecosystems [Schröter *et al.* 2014]. Furthermore, the advantage of a remote sensing analysis allows for covering the gap in evaluating the extension and conditions of the ecosystem in time and space, where there is constant regeneration and extraction of the *ANPP* [Vargas *et al.* 2019]. Under these considerations, the high Andean wetlands are quite vulnerable. In addition to being dependent on environmental factors, higher extraction than regeneration is reported (example: overgrazing and peat extraction). It means that there is overdemand and the capacity is exceeded [Caro *et al.* 2014; Cochi-Machaca *et al.* 2018]. Therefore, it is necessary to conserve the wetlands to avoid depletion and degradation [Moreau *et al.* 2003]. The use of remote sensing, as shown in this study, helps to assess the capacity and patterns of extraction and regeneration in these ecosystems, as well as monitoring temporal and spatial changes to safeguard ecosystem services for the future [Vargas *et al.* 2019]. Likewise, the information generated is also useful to complement both economic and sociocultural evaluations of ecosystem services to improve decision-making when managing the territory [Cano, Haller 2018; Lozano Lazo 2021].

CONCLUSIONS

The use of remote sensing and the application of the Monteith model (1972) helped to quantify the supply of the *ANPP* from high Andean wetlands (called bofedales). This provides prediction and presents a very consistent response, where the possibility of estimation through the use of the fraction of absorbed photosynthetically active radiation (f*PAR*) and absorbed photosynthetically active radiation (*APAR*) amounts to 52%. In the application of the model, the intra-annual temporary aboveground net primary productivity (*ANPP*) supply capacity presents a maximum average of 160.54 kg DM·ha^{-1}·month^{-1} in the rainy season (December–May) and a maximum average of 81.17 kg DM·ha^{-1}·month^{-1} in the dry season (June–October). In 2003–2020, the interannual temporary capacity presented approximate minimum and maximum values of 1100–1700 kg DM·ha^{-1}·year^{-1} respectively. Furthermore, the analysis carried out with remote sensors shows a seasonal variability consistent with what was found in the field. This is consistent with the climatic and seasonal variations typical of Andean ecosystems.

The study provided methodological information and valuable results for the quantification of the capacity to supply the *ANPP* in the high Andean wetlands; this is an important indicator for the biophysical evaluation of ecosystem services on a temporal and spatial scale using remote sensing. This information helps to maintain the sustainability of wetlands and prevent their depletion, degradation, and it reduces the risk of loss and may have positive impact on other ecosystem services. Furthermore, it can support the implementation of adequate management measures, such as livestock production management, animal carrying capacity, forage budget, state and health of the ecosystem, maintenance of biodiversity, conservation of higher trophic levels, among other purposes.

This study used models from other investigations applied to other types of vegetation covers. It is necessary to generate field data applied to this type of ecosystem, especially in the estimation of the f*PAR* and normalized difference vegetation index (*NDVI*) localised. It is necessary to keep in mind that the *ANPP* was estimated with uncontrolled inaccuracies; a large part of errors are in the cuts, as well as in the noise presented by the remote sensors, where the impact of clouds limit the investigation possibility at these latitudes. If it is required to be more precise in the estimation of solar radiation measured with remote sensors compared to data collected in the field, the use of sophisticated and more accurate instruments and technology is necessary. Furthermore, it is essential to generate individual models for mountain ecosystems, including their coverage, such as grasslands, wetlands, and high Andean forests. In the same way, there is no doubt that other factors could be included, such as climatic, edaphological, biological, or anthropic that can enrich the model in contrast to remote sensors and that would track the management of wetlands over time.

Finally, it is advisable to carry out this type of study at a regional and macro-regional scales due to the heterogeneous nature of Andean ecosystems. Likewise, it is necessary to integrate these results with economic and sociocultural evaluations of ecosystem services, taking into account climate change and the anthropogenic activities typical of these vulnerable ecosystems. This allows to improve accounting, capacity evaluation, and above all, the management of ecosystem resources and their environment.

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