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Scientific Article
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Net primary productivity of soybean using different data sources and estimation methods[1]

Produtividade primária líquida da soja utilizando diferentes fontes de dados e métodos de estimativa

Grazieli Rodigheri[2]*, Denise Cybis Fontana[2], Genei Antonio Dalmago[3], Laura Pigatto Schaparini[4], Juliano Schirmbeck[5], José Maurício Cunha Fernandes[3]

ABSTRACT - Net primary productivity (NPP) can be used to quantify the relative role of climate and human activities in vegetation dynamics. Given its importance, many NPP estimation models have been developed, but some of the required data is still limited. Therefore, this study aimed to estimate the potential and actual NPP by testing different approaches regarding the data source and estimation methods and evaluate the human appropriation of NPP (HANPP) in a soybean field cultivated in southern Brazil. For this, data were obtained from field-measured NPP in soybean cultivation in Carazinho, Rio Grande do Sul, Brazil, and compared to the potential and actual NPP estimations using the CASA model and data from ERA-Interim. Subsequently, land use changes due to agricultural activities were evaluated from the potential and actual NPP through HANPP. No significant difference was observed associated with the used data sources, showing that the ERA-Interim reanalysis weather data can be employed for this purpose. The actual NPP estimations by the CASA model were consistent with a high association with the data measured in the field. HANPP, through only one annual soybean cultivation, represented 29% of the potential NPP in the region. It indicates the potential to increase intensification with annual crops in the region.

Key words: CASA model. NDVI. HANPP. ERA-Interim.

RESUMO - A Produtividade Primária Líquida (NPP) pode ser utilizada para quantificar o papel relativo do clima e das atividades humanas na dinâmica da vegetação. Dada sua importância, muitos modelos de estimativa de NPP foram desenvolvidos, mas parte dos dados requeridos, ainda são limitados. Diante disso, este trabalho teve como objetivo estimar a NPP potencial e real testando diferentes abordagens quanto a fonte dos dados e métodos de estimativa, assim como, avaliar a apropriação humana da NPP em uma lavoura de soja cultivada no Sul do Brasil. Para isso, foram obtidos dados de NPP medida a campo em cultivo de soja em Carazinho, no Rio Grande do Sul, e comparados às estimativas de NPP potencial e NPP real, utilizando o modelo CASA e dados do ERA-Interim. Posteriormente, com a NPP potencial e real foram avaliadas as mudanças causadas pelo uso da terra em função das atividades agrícolas, através da Apropriação Humana da NPP (HANPP). Verificou-se que não houve diferença significativa associadas às fontes de dados utilizadas, evidenciando que os dados meteorológicos de reanálise do ERA-Interim podem ser utilizados para esse fim. As estimativas da NPP real pelo modelo CASA foram consistentes com elevada associação aos dados medidos a campo. A HANPP por meio de apenas um cultivo anual de soja, representou 29% do potencial de NPP na região. Isso indica que há potencial para elevar a intensificação com cultivos anuais na região.

Palavras-chave: Modelo CASA. NDVI. HANPP. ERA-Interim.

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*Author for correspondence
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[1]Parte da Dissertação do primeiro autor, apresentada ao Curso de Pós-Graduação em Sensoriamento Remoto, da Universidade Federal do Rio Grande do Sul (UFRGS)

[2]Programa de Pós-Graduação em Sensoriamento Remoto, Universidade Federal do Rio Grande do Sul (UFRGS), Porto Alegre-RS, Brasil, grazielirodigheri@gmail.com (ORCID ID 0000-0002-9916-1167), dfontana@ufrgs.br (ORCID ID 0000-0002-2635-6086)

[3]Embrapa Trigo, Passo Fundo-RS, Brasil, genei.dalmago@embrapa.br (ORCID ID 0000-0003-0102-3733), mauricio.fernandes@embrapa.br (ORCID ID 0000-0003-4965-2432)

[4]Programa de Pós-Graduação em Fitotecnia, Universidade Federal do Rio Grande do Sul (UFRGS), Porto Alegre-RS, Brasil, laura_pigatto@yahoo.com.br (ORCID ID 0000-0003-4799-7496)

[5]Universidade do Vale do Taquari (UNIVATES), Lajeado-RS, Brasil, schirmbeck.j@gmail.com (ORCID ID 0000-0001-9342-5144)

INTRODUCTION

The net primary productivity (NPP) of ecosystems is an important tool to identify the magnitude and causes of gaps in agricultural production. It has become especially important given the projected need for a 50% increase in food production by 2050 to feed the growing population (FAO, 2017). NPP refers to the amount of carbon fixed through photosynthesis by a plant community per unit of time and space (GAO *et al*., 2013; PEI *et al*., 2013; TAELMAN *et al*., 2016; ZHU *et al*., 2017). NPP is an indicator of vegetation growth, ecosystem health (CHEN *et al*., 2019; RUNNING *et al*., 2004; TAELMAN *et al*., 2016), and soil degradation (ZHOU *et al*., 2017). This information can provide valuable guidance for the management of agroecosystems (YIN *et al*., 2020), especially to identify the potential for intensification in cultivated areas.

Two parameters are important in the study of ecosystem productivity: the natural potential NPP (NPP_p), which represents the potential growth conditions of natural vegetation in the absence of human interference (SOUZA; MALHI, 2017; KRAUSMANN *et al*., 2013; LOREL *et al*., 2019), and the actual NPP (NPP_a), which represents the actual situation of vegetation productivity, which can be controlled by the climate and also human activities (SOUZA; MALHI, 2017). The most obvious anthropogenic influence is related to changes in land use and types of cover, which alter the natural environment (RUNNING *et al*., 2004). In this context, the concept of human appropriation of NPP (HANPP) emerges, which is an important parameter, and refers to the proportion of the annual production of natural plant biomass appropriated by human activities (HABERL; ERB; KRAUSMANN, 2014). HANPP can be determined by relation between the NPP_p and the NPP_a (LI *et al*., 2018; ZHOU *et al*., 2017).

The Carnegie-Ames-Stanford Approach (CASA) model, developed by Potter *et al*. (1993), stands out among the NPP simulation models most widely used in the last decades. The main modification that the model has undergone is the incorporation of remote sensing (RS) data (BAO *et al*., 2016; PEI *et al*., 2013), seeking to increase the ability to study ecosystems with higher precision and detail, less cost, and visualization of remote locations (LEES *et al*., 2018).

A major challenge for applying NPP estimation models is the availability of measured weather data both in time scale and in spatial density, given the limitations (BATTISTI; BENDER; SENTELHAS, 2019). For this reason, data from products of reanalysis become important, as they can serve as complementary or even substitutes for the measured data but require local validations. The ERA-Interim, produced by the European Centre for Medium-Range Weather Forecasts (ECMWF), is among the most recent atmospheric reanalyses that offer weather data with global coverage. The products available include a variety of surface and upper air parameters (DEE *et al*., 2011), and these data can help to improve global NPP estimations.

The improvement of NPP estimation methods can assist in quantifying the individual effects of human factors and climate variations (LI *et al*., 2016), identifying where and how these factors affect the dynamics of agricultural cultivations. This study aimed to evaluate different approaches regarding the data source and methods for estimating potential and actual NPP and evaluate the human appropriation of NPP in a soybean field cultivated in southern Brazil.

MATERIAL AND METHODS

General flowchart of the study

The main data and development stages applied in this study are described in the following flowchart (Figure 1).

Study area

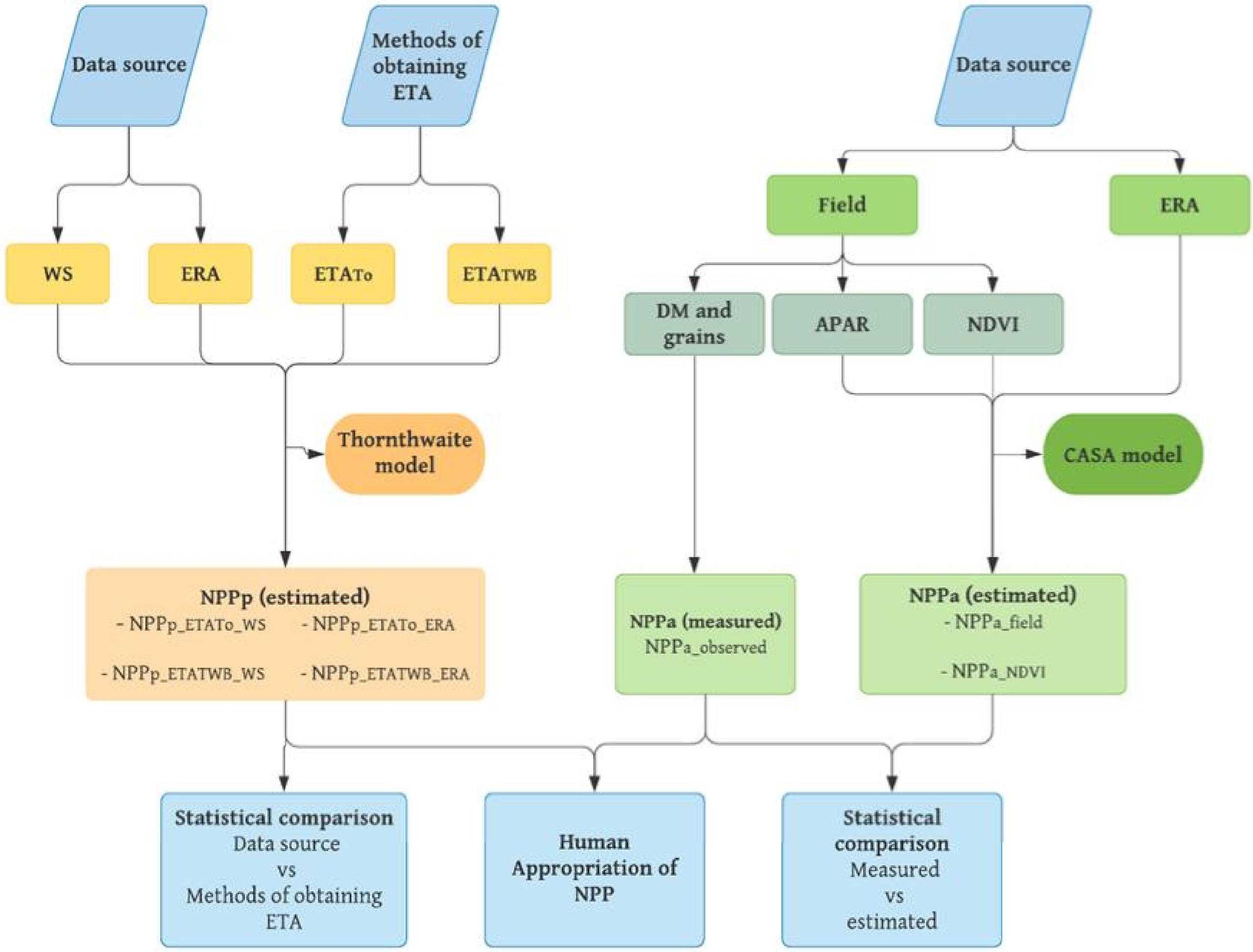
The study area is located in the municipality of Carazinho, in the north of the State of Rio Grande do Sul, Brazil (28°13′43.89″ S and 52°54′15.93″ W, with an elevation of 560 m). It is a commercial property that cultivates soybean and develops research in partnership with the Brazilian Agricultural Research Corporation (Embrapa Wheat). The property Capão Grande is located in a region of intense agricultural activity in Rio Grande do Sul, whose main crop is soybean.

According to the climate classification of Köppen (1936), the regional climate is Cfa, that is, a subtropical climate predominantly temperate, mesothermal, and humid, with a mean air temperature of the hottest month above 22 °C. It has a well-defined winter and summer season, without a dry season, but with high interannual and spatial variability, especially in the summer.

Weather data

The weather data were obtained from two sources: (i) weather station (WS) of the Brazilian National Institute of Meteorology (INMET), located in Passo Fundo (28°13′37.09″ S and 52°24′12.44″ W, with an elevation of 670 m), representing the regional climate condition; and (ii) ERA-Interim (ERA) reanalysis data, for the geographic coordinate of the property, made available by ECMWF and extracted through scripts using the interactive data language (IDL). WS and ERA data were obtained to simulate local measurements and extrapolation to the region, respectively.

Figure 1 - General flowchart of the study with the main developed stages



The weather elements used for both data sources consisted of rainfall (mm), air temperature (°C), relative humidity (%), wind speed (m s^{-1}), and global solar radiation (MJ m^{-2} day^{-1}). Subsequently, the meteorological water balance (WB) (THORNTHWAITE; MATHER, 1955) and potential evapotranspiration (ETP) were calculated using the Penman-Monteith method (ALLEN *et al*., 1998), with the available water storage capacity (AWC) defined as 75 mm, as observed by Cunha *et al*. (2001).

Field data

The soybean cultivar DM 5958 RSF IPRO was used in the field experiment, with sowing on 11/13/2017 and harvest on 4/3/2018. The components of the incident (PAR_{inc}), transmitted (PAR_t), and reflected photosynthetically active radiation (PAR_{ref}) of the crop were measured during the experimental period. PAR_{inc} was measured by an SQ-110 sensor (Apogee Instruments, Logan, UT, USA). PAR_t and PAR_{ref} were measured using manufactured sensors of one meter in length with five cells of amorphous silicon arranged in parallel and spaced at 20 cm (CHARTIER *et al*., 1989). PAR_t was measured at 5 cm above the ground using five sensors, while PAR_{ref} was measured with six sensors installed at 1.5 m above the ground, with the sensors facing the canopy. The sensors were connected to an AM16 32B channel multiplexer, which was coupled to a CR 1000 datalogger, both from Campbell Scientific, Inc. The datalogger was programmed to perform continuous readings throughout the soybean cycle every 30 seconds and the means were stored every 15 minutes. The absorbed PAR (APAR) (MJ m^{-2} day^{-1}) was determined from these data by Equation (1) and later totaled for the month, according Dalmago *et al*. (2018):

$$APAR = PAR_{inc} - PAR_t - PAR_{ref} \quad (1)$$

The fraction of PAR absorbed by vegetation (FPAR) was calculated by Equation (2).

$$FPAR = \frac{APAR}{PAR_{inc}} \quad (2)$$

In addition, the normalized difference vegetation index (NDVI), proposed by Rouse *et al*. (1973), was used to adjust functions to estimate FPAR as a function of NDVI. NDVI was obtained with the incident (Decagon SRS-NDVI Hemispherical) and reflected radiation sensors (Decagon SRS-NDVI with Vision Limiter) in the red (0.6 to 0.7 µm) and near-infrared (NIR) spectrum (0.805 a 0.815 µm). These spectral sensors were installed on a mast in the center of the experimental area at a height of 1 m above the top of the canopy, being adjustable throughout the soybean cycle. Data were collected at three different points of the crop at 15-minute intervals, using only the mean data of 10:15, 10:30, 10:45 am, corresponding to the data obtained during Landsat satellite passages.

The dry matter (DM) accumulated by the soybean crop was determined weekly from plant emergence to the end of the crop cycle. For this, four replicates of a linear meter of plants were collected in sections of rows in the central transect of the area reserved for evaluations. The green biomass was placed in paper packaging and taken to an oven to dry the plant material at a temperature of 70 °C until constant mass. The DM was weighed and expressed in g m^{-2}. Four 9-m^2 biomass samples were taken after physiological maturation to determine grain productivity. The grains from each plot were separated from impurities and weighed. Grain productivity was corrected at 13% moisture and expressed in kg ha^{-1}.

All biological data were transformed into a carbon unit using a conversion factor of 0.40 (PILLON; MIELNICZUK; MARTIN NETO, 2004).

NPP_p estimation

The Thornthwaite Memorial model (LIETH, 1975) was used in the estimation of the natural potential NPP (NPP_p) as an exponential function of actual evapotranspiration, according to Equations (3) to (5):

$$NPP_p = 3000\left[1 - e^{-(0.0009696\times(v-20))}\right] \quad (3)$$

$$V = \frac{1.05r}{\sqrt{1+(1+1.05r/L)^2}} \quad (4)$$

$$L = 3000 + 25t + 0.05t^3 \quad (5)$$

where NPP_p is the annual natural potential NPP expressed in g m^{-2} $year^{-1}$, *e* is the basis of the natural logarithm, 3,000 is a constant and refers to the maximum NPP achieved in different environments on Earth, *v* is the actual evapotranspiration (ETA) (mm), *L* is the mean annual potential evapotranspiration (ETP) (mm), *r* is the total annual rainfall, and *t* is the mean annual air temperature (°C).

The ETA for the proposed model (Equation 3) was obtained using two approaches. Equations (4) and (5) were used in the first approach, being defined as the original Thornthwaite Memorial ETA (ETA_{To}). In the second approach, ETA was obtained as a variable derived from the water balance, being defined as the WB Thornthwaite Memorial ETA (ETA_{TWB}).

Two sources of input weather data were evaluated for each method of obtaining ETA: WS and ERA. In this sense, NPP_p estimations for the different methods of obtaining ETA and the different data sources were called $NPP_{p\_ETATWB\_ERA}$, $NPP_{p\_ETATWB\_WS}$, $NPP_{p\_ETATo\_ERA}$, and $NPP_{p\_ETATo\_WS}$ and obtained for 10 years (2009 to 2018).

The NPP_p estimations were statistically analyzed using the Student's t-test, considering 10 years as replications to compare the databases and the ETA estimation methods at a 5% probability error.

Changes in NPP_p estimations were performed by comparing the annual pattern of these estimations as a function of variations in the weather conditions of annual air temperature and rainfall from 2009 to 2018. For this, the used rainfall air temperature data were obtained through the mean between WS and ERA.

NPP_a estimation

The actual NPP (NPP_a) was estimated using the CASA model, which considers NPP as a variant of the radiation use efficiency (RUE) model, originally proposed by Monteith (1972). For that, the APAR data used in the model were obtained through two different approaches. In the first approach, the APAR data obtained from field measurements were used, being named $APAR_{field}$. In the second approach, APAR was obtained through global solar radiation data derived from ERA (RG_{ERA}) and NDVI and FPAR data were measured in the field, according to Equations (6) and (7), being called $APAR_{NDVI}$.

$$APAR_{NDVI} = RG_{ERA} \times 0.5 \times FPAR \quad (6)$$

$$FPAR = 1.1755 \times NDVI - 0.14 \quad (7)$$

where FPAR results from the adjustment of a linear regression between FPAR and NDVI measured in the field, with an R^2 of 0.98. The 0.5 coefficient represents the proportion of the total solar radiation available for vegetation (PEI *et al*., 2013; ZHU *et al*., 2017).

In the CASA model, NPP_a (g C m^{-2} $year^{-1}$) is the product of APAR (MJ m^{-2}) by RUE (g C MJ^{-1}) adapted from Potter *et al*. (1993), according to Equation (8).

$$NPP_{r(i)} = APAR_{(i)} \times RUE \quad (8)$$

where indices *i* and *ii* associate NPP_a and APAR, respectively, to the way of obtaining: NPP_{a_field} obtained using $APAR_{field}$ and NPP_{a_NDVI} obtained using $APAR_{NDVI}$.

RUE was estimated from a maximum conversion efficiency constant (RUE_{max}), adjusted to limiting factors (Equation 9), such as air temperature and water condition of the environment (BAO *et al*., 2016; ZHOU *et al*., 2017).

$$RUE = RUE_{max} \times T_{\varepsilon 1} \times T_{\varepsilon 2} \times W_{\varepsilon} \quad (9)$$

The constant RUE_{max} was obtained from the slope, resulting from the linear relationship between DM and $APAR_{NDVI}$. The terms $T_{\varepsilon 1}$ and $T_{\varepsilon 2}$ denote coefficients of thermal stress, which were calculated using the mean monthly air temperature (T) (°C) for $T_{\varepsilon 1}$ and optimal temperature for plant growth (T_{opt}) (°C) for $T_{\varepsilon 2}$, which is the mean air temperature during the month of maximum NDVI (POTTER *et al.*, 1993), both obtained from the ERA data. The term W_{ε} is the coefficient of water stress, being calculated by the ratio between ETA_{TWB} and ETP, obtained through the ERA data. More information on mathematical functions can be found in Potter *et al*. (1993) and Yu *et al*. (2011).

The validation of the estimated NPP_{a_field} and NPP_{a_NDVI} data though the CASA model used DM data measured in the experiment, considering them as observed NPP_a data ($NPP_{a\_observed}$).

The data and estimations of NPP_{a_field}, NPP_{a_NDVI}, and $NPP_{a\_observed}$ were obtained only for the period of the field experiment but counted as being annual values, which could represent conditions of only one cycle in the year for the region.

Estimation of human appropriation of NPP

The HANPP estimation in carbon units (C) is the sum of two subcategories: $HANPP_{luc}$ and $HANPP_{harv}$ (KRAUSMANN *et al.*, 2013). $HANPP_{harv}$ is the amount of carbon harvested by humans as biomass (KRAUSMANN *et al.*, 2013; LOREL *et al.*, 2019), obtained from grain productivity and measured at the end of the soybean cycle. It represented the part harvested and used by humans. In addition, $HANPP_{luc}$ refers to the result of land-use changes induced by humans (KRAUSMANN *et al.*, 2013; LOREL *et al.*, 2019), calculated by the difference between the mean of the annual estimations of $NPP_{p\_ETATWB\_ERA}$ ($NPP_{p\_ETATWB\_ERA\_m}$) and $NPP_{a\_observed}$ (Equation 10).

$$HANPP_{luc} = NPP_{p\_ETATWB\_ERA\_m} - NPP_{a\_observed} \quad (10)$$

Only $NPP_{p\_ETATWB\_ERA}$ estimation was used because no difference was observed between the used data sources after analyzing the $NPP_{p\_ETATWB\_ERA}$, $NPP_{p\_ETATWB\_WS}$, $NPP_{p\_ETATo\_ERA}$, and $NPP_{p\_ETATo\_WS}$ estimations. Thus, the estimation using the ERA data was selected, as they are spatialized data with a higher sampling frequency than conventional networks. In addition, the estimates obtained using the ETA_{TWB} method was used because, unlike the ETA_{To} method, this method takes into account weather elements such as global solar radiation, relative air humidity, and wind speed, better characterizing the evaporative flow of the region.

RESULTS AND DISCUSSION

NPP_p estimations

The highest variability in the $NPP_{p\_ETATWB\_ERA}$, $NPP_{p\_ETATWB\_WS}$, $NPP_{p\_ETATo\_ERA}$, and $NPP_{p\_ETATo\_WS}$ estimations in each year was associated with the method of calculating ETA, either using ETA_{To} or ETA_{TWB}. Moreover, the input data sources in the WS and ERA models generated similar results for the same method.

The interaction between the different estimations had no significant difference between the data sources WS and ERA, evidencing the accuracy of the ERA data compared to WS ($p > 0.05$) (Table 1). It indicates that ERA reanalysis data can be used to estimate NPP_p from different locations in southern Brazil. The observed result is mainly important to improve NPP_p estimations in regions that have a shortage or lack of weather stations, which represents a potential source of uncertainty. Moreover, reanalysis data provide a multivariate, spatially complete, and coherent record of global atmospheric circulation (DEE *et al.*, 2011). As a dataset, reanalysis offers a number of significant advantages over surface station observations: a complete, long-term time-series, without discontinuity (KUBIK *et al*., 2013), besides providing repeatability, systematic collection and information on their spatial distribution.

Table 1 - Evaluation of the potential NPP (NPP_p) for the data sources of ERA-Interim (ERA) and weather station (WS) and the NPP_p calculation methods using the actual evapotranspiration (ETA), original (ETA_{To}) and water balance (ETA_{TWB}) Thornthwaite Memorial

Data source	ETA calculation method	
	ETA_{To}	ETA_{TWB}
WS	871.48 ± 57.56	790.93 ± 32.06
ERA	856.05 ± 54.68	802.66 ± 12.67

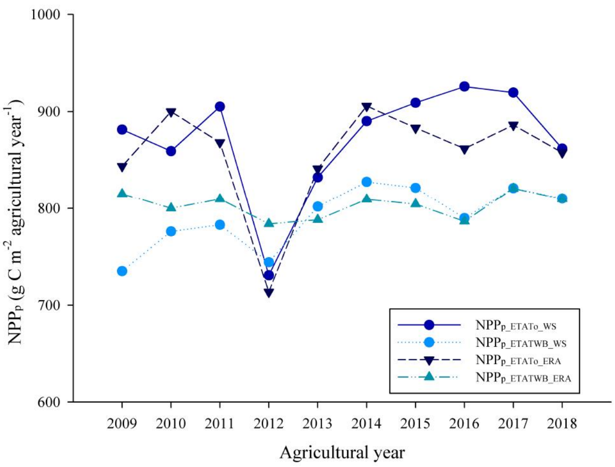
Mean values of analysis performed for the 10 agricultural years ± standard deviation. Data source p-value = 0.9156 and calculation method p-value = $3.672e^{-05}$

A significant difference was observed between the ETR calculation methods in the mean NPP_p estimation by the Thornthwaite Memorial model ($p < 0.05$). In general, the ETA_{TWB} method generated mean values 7.5% lower than obtained using the ETA_{To} method. These differences are probably associated with the fact that the ETA_{To} method considers only the effects of rainfall and air temperature in the NPP_p estimation, ignoring other climate factors (YIN *et al*., 2020), while the ETA_{TWB} method takes into account five weather elements (air humidity, rainfall, air temperature, wind speed, and solar radiation) in the NPP_p estimation. The ETA_{TWB} method can characterize better the evaporative flow of a given region because it uses more weather elements and, therefore, the NPP_p estimations tend to be more accurate.

It is also observed in the annual variability of the $NPP_{p\_ETATWB\_ERA}$, $NPP_{p\_ETATWB\_WS}$, $NPP_{p\_ETATo\_ERA}$, and $NPP_{p\_ETATo\_WS}$ estimations, in which the NPP_p data estimated by the ETA_{To} method showed results far superior to those estimated by the ETA_{TWB} method. On the other hand, both sources of input data in the model (WS and ERA) produced very similar annual NPP_p profiles (Figure 2), with a similar pattern in most years, except for small variations that occurred mainly in 2009, 2010, and 2016.

The analysis of the rainfall and air temperature pattern showed that the $NPP_{p\_ETATWB\_ERA}$, $NPP_{p\_ETATWB\_WS}$, $NPP_{p\_ETATo\_ERA}$, and $NPP_{p\_ETATo\_WS}$ estimations were very similar to the water regime of the study period (Figures 2 and 3). A high variation was observed in the annual rainfall regime in the region, with the highest water restriction in 2012, the same year as the lowest NPP_p estimations, mainly when using the ETA_{To} method (Figure 2). Other authors have also reported similar results, such as Zhang *et al*. (2020), who observed that the humidity levels, resulting from rainfall, were determinant in the potential NPP for the ETA_{To} model, controlling NPP_p variations in a direct relationship with rainfall.

Figure 2 - Potential net primary productivity (NPP_p) calculated with the actual evapotranspiration estimated by the original (ETA_{To}) and water balance Thornthwaite Memorial model (ETA_{TWB}), both with weather data obtained from the INMET Automatic Weather Station (WS) and ERA-Interim (ERA) reanalysis data



It is widely known that rainfall is an important factor that regulates NPP_p and its variation, especially in dry regions (CHEN *et al*., 2014; PIAO *et al*., 2012). The decrease in rainfall can lead to a reduction in photosynthetic activity and biomass production by plants (GESSNER *et al*., 2013), inhibiting their growth. Another important factor is that soil water content is a key element, directly related to rainfall and NPP_p. Thus, an increase in rainfall can increase soil water content and benefit vegetation growth (CHEN *et al*, 2019).

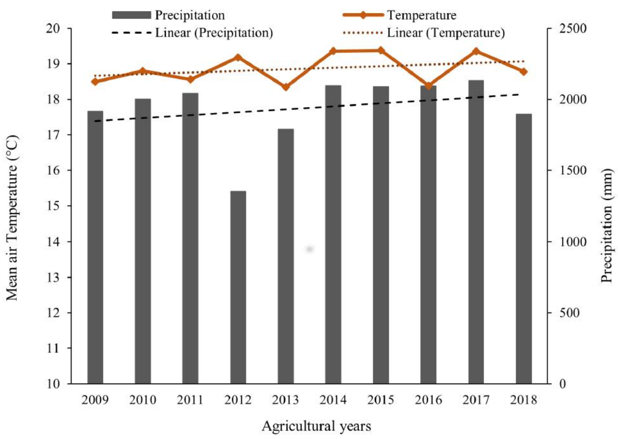
Climate variability may directly influence vegetation growth, as changes in air temperature and rainfall can determine the hydrothermal conditions of vegetation growth, especially for dry ecosystems (LI *et al*., 2015). Changes occurred mainly for rainfall in the present study, resulting in impacts that were perceptible by NPP_p oscillations in the analyzed period.

The NPP_p estimations were not significantly influenced by rainfall variations when using the ETA calculated by ETA_{TWB} (Figure 2). It probably occurred because the ETA_{TWB} method characterizes better the weather conditions, as previously mentioned.

NPP_a estimations

The main difference between the NPP_{a_field} and NPP_{a_NDVI} estimations found by using the CASA model regarding $NPP_{a\_observed}$ consisted of the magnitude of the model values, while the monthly time profile was quite similar for the different approaches. The

Figure 3 - Total annual rainfall and mean air temperature for the 2009 to 2018 agricultural years. Carazinho, RS, Brazil



CASA model underestimated $NPP_{a\_observed}$ by more than 40 g C m^{-2} (20%) especially at the stage of full soybean development. The soybean $NPP_{a\_observed}$ reached approximately 203 g C m^{-2} $month^{-1}$ during the maximum crop growth, but the estimations of the CASA model for NPP_{a_field} and NPP_{a_NDVI} reached only 163 and 149 g C m^{-2} $month^{-1}$, respectively (Figure 4).

The correlation between the results of $NPP_{a\_observed}$ and the NPP_{a_field} and NPP_{a_NDVI} estimations was high ($r = 0.92$ and 0.95), indicating a very consistent correspondence between the estimations performed by the CASA model with the data observed in the field (Table 2). The correlation found in the present study was higher than that obtained in similar studies. Chen *et al.* (2019) evaluated the performance of the CASA model to simulate NPP_a compared to the measurement in the field and obtained an R^2 of 0.74 ($p < 0.001$). The authors concluded that the NPP_a estimated by the CASA model was reliable and could be applied in future stages and analyses. Other authors have also obtained satisfactory results using the CASA model to estimate NPP_a. Yan *et al.* (2019) observed good agreement between the calculated and measured NPP_a values, with Pearson correlation coefficient $r = 0.786$ ($p < 0.001$), and concluded that the results indicate that the NPP_a of arable lands in China was calculated with precision. Li *et al.* (2016), comparing the observed NPP and the CASA simulation results, showed good agreement between both ($R^2 = 0.750$, $p < 0.01$). The authors concluded the simulation accuracy of the model was satisfactory for the needs of the study.

The comparison between the NPP_{a_field}, NPP_{a_NDVI}, and $NPP_{a\_observed}$ estimations and the results of other researchers who used similar approaches showed similar patterns. Gao *et al.* (2013) studied the vegetation NPP_a on the Tibetan plateau and reported that the validation of the modeled NPP_a was approximately 35% lower than the measured NPP_a. In the present study, the difference between the NPP_{a_field} and NPP_{a_NDVI} estimations and $NPP_{a\_observed}$ for soybean was 15 and 27%, respectively. Piana and Civeira (2017) simulated the soybean NPP_a for regions of the Pampa biome in Argentina, between 1993 and 2005, and found average values of 210 g C m^{-2} $year^{-1}$ (2.1 ± 0.1 t ha^{-1} $year^{-1}$). On the other hand, Civeira (2016) studied the NPP_a of several crops in the periurban areas (south, north and west) of Buenos Aires City, Argentina, and found maximum values of 320 g C m^{-2} $year^{-1}$ (3.2 t ha^{-1} $year^{-1}$) for soybean.

Given the consistency of the results, the proposed approach, employing data from reanalysis and satellite images, highlights one of the great

Figure 4 - Time profile (a) and dispersion (b) between the net primary productivity observed in the field ($NPP_{a\_observed}$) and estimated using data from $APAR_{field}$ (NPP_{a_field}) and $APAR_{NDVI}$ (NPP_{a_NDVI}) for soybean cultivation

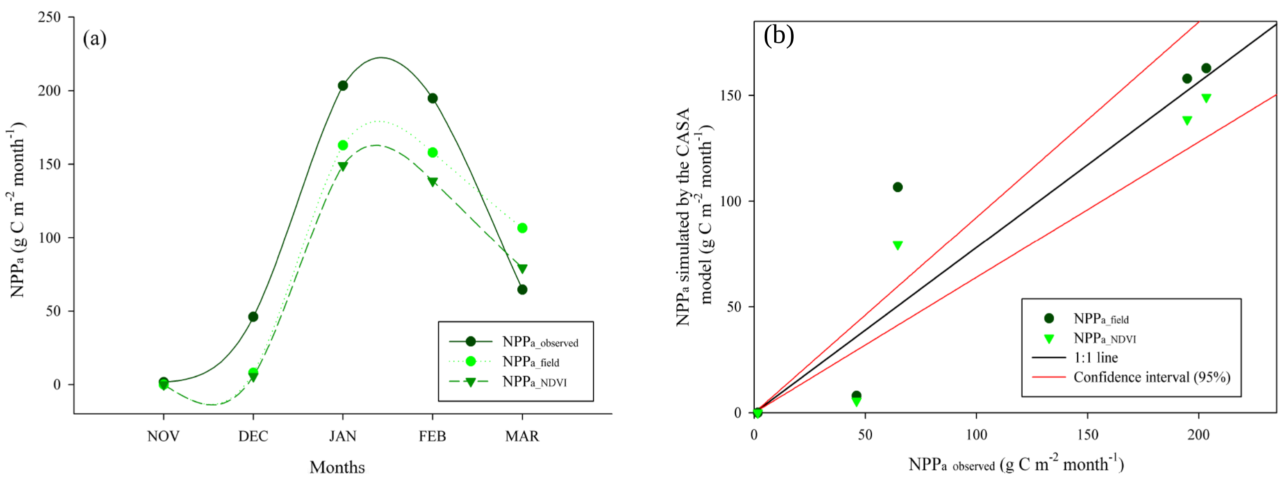


Table 2 - Total NPP_a obtained with data from $APAR_{field}$ (NPP_{a_field}) and $APAR_{NDVI}$ (NPP_{a_NDVI}), correlation coefficient (r) and root-mean-square error of the estimates (RMSE) of NPP_{a_field} and NPP_{a_NDVI} obtained by the CASA model relative to the NPP_a observed in the field ($NPP_{a\_observed}$)**

	Σ NPP_a (g C m^{-2})	r	RMSE
NPP_{a_field}	435.5	0.92	35.3
NPP_{a_NDVI}	372.9	0.95	39.9

** The total $NPP_{a\_observed}$ was equal to 510.4 g C m^{-2}

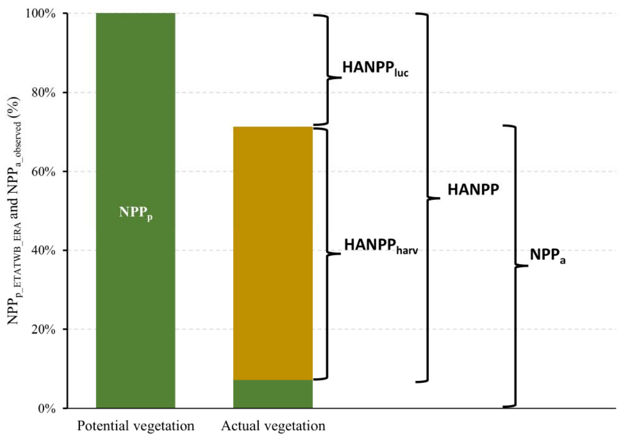
advantages of using the CASA model, which is the possibility of representing spatial variations of NPP_a in producing regions, whose degree of detail depends only on the spatial resolution of the selected remote sensor. Maps depicting the spatial variability of NPP_a in different regions of the globe have been observed in several studies (BAEZA; PARUELO, 2018; LIANG *et al.*, 2015; LIU *et al*., 2019; YIN *et al*., 2020).

HANPP quantification

According to the $NPP_{a\_ETATWB\_ERA\_m}$ and $NPP_{a\_observed}$ estimations, $HANPP_{luc}$, derived only from land use and coverage by human activities, reached 29%. It shows that, when only one annual cultivation is carried out, about one-third of the potential primary production of the ecosystem was appropriated by human activities associated with grain cultivation in the area (Figure 5). Thus, a $HANPP_{luc}$ of 29% also indicates a potential for vegetation that can still be exploited in the area by introducing other annual crops or increasing the productivity of crops already existing there. However, the long-term sustainability of this agroecosystem must be considered whatever measures are proposed to harness this existing potential.

The $HANPP_{luc}$ estimations based on NPP_{a_field} and NPP_{a_NDVI} estimations by the CASA model were higher than the $HANPP_{luc}$ calculated from the $NPP_{a\_observed}$, reaching up to half of the $NPP_{p\_ETATWB\_ERA\_m}$ (46 and 54%, respectively). Haberl *et al.* (2007) evaluated HANPP for different activities and found that most appropriation was associated with agricultural production. These authors also identified in Austria that approximately 50% of global HANPP was related to arable lands.

Figure 5 - Potential net primary productivity estimation using the ETA_{TWB} method and ERA data ($NPP_{p\_ETATWB\_ERA\_m}$), NPPa observed in the field ($NPP_{a\_observed}$), human appropriation of NPP by land use ($HANPP_{luc}$), and harvested NPP ($HANPP_{harv}$) based on Haberl, Erb, and Krausmann (2014)



Baeza and Paruelo (2018) studied the HANPP variation in the Rio de la Plata (RPG) fields in southern South America, including the Pampas in Argentina and fields in Uruguay and southern Brazil for two agricultural cultivations from 2001/2002 to 2012/2013 and identified an increase in the total HANPP, which was related to an increase in the vegetation fraction harvested by humans ($HANPP_{harv}$) in the same period. However, these authors also observed a marked decrease of $HANPP_{luc}$ in 2012/2013, reaching negative values in some regions of RPG. This pattern of decrease resulted not only from the reduction in NPP_p but also due to increased productivity and expansion of the double growing season, that is, two annual cultivations.

Annual production in much of Brazil is made up of more than one agricultural cultivation. In general, winter cereals such as wheat, oat, barley, and pastures such as ryegrass and canola are also grown in the study region (July to October). These crops, grown in the same area as soybean in succession, contribute to increasing the NPP_a produced throughout the year, making losses related to land-use change (inappropriate NPP_a) lower than those observed. The NPP_a may be higher than the environment NPP_p under these conditions of two or more annual crops.

The appropriation of $NPP_{a\_observed}$ as a function of crop removal ($HANPP_{harv}$) leaves in the field only the harvested material not used for human consumption and available in the agroecosystem. Thus, land-use changes, through the introduction and harvest of agricultural cultivations, increase the share of primary production destined for human consumption, decreasing the fraction available for other functions of the ecosystem (DEFRIES; FOLEY; ASNER, 2004). In this context, agricultural practices that aim to maintain continuous soil coverage, minimum disturbances, and crop rotation (SOARES *et al*., 2020) are required to minimize the effects of human appropriation due to the harvest of biomass.

The HANPP evaluation has great importance, as it allows relating the potential productivity of an ecosystem in the absence of human interferences (HABERL; ERB; KRAUSMANN, 2014), with the current agricultural production of the formed agroecosystem due to land-use changes (KRAUSMANN *et al*., 2013). The analysis of parameters such as NPP_p, NPP_a, and HANPP, estimated by theoretical models, can be used not only to indicate the relative contribution of natural and anthropogenic factors (LI *et al*., 2018) but also to direct regulation (FENG *et al*., 2017) and agricultural intensification in current and future scenarios. In this sense, more studies should be conducted to evaluate the effects of human activities and climate variations on the NPP of agroecosystems. Production gaps need to be filled considering the long-term sustainability of agroecosystems aiming at adequate management of environmental resources necessary to maintain agricultural production, minimizing the environmental impacts associated with these activities (TAELMAN *et al*., 2016; WEINZETTEL; VAČKÁŘŎ; MEDKOVÁ, 2019).

CONCLUSIONS

1. Estimations of natural potential NPP show sensitivity to the method of obtaining ETA and reflect the influence of interannual variations in weather conditions on the growth potential of vegetation in the absence of human interference;
2. The ERA-Interim reanalysis weather data can be used as input data in the Thornthwaite Memorial model for estimating the potential NPP and in the CASA model for estimating the actual NPP, considering the similarity of the data measured on the surface, with the advantage of allowing higher spatial detailing of the models compared to that possible using interpolated data from surface weather stations;
3. The CASA model generates accurate estimates of the actual NPP, providing a means to evaluate the dynamics of carbon fixation through photosynthesis throughout the production cycle of crops;
4. The study of human appropriation of NPP is efficient in identifying losses or gains in biological productivity in an ecosystem that has been modified by human activities. The evaluation of $HANPP_{luc}$ and $HANPP_{harv}$ allows identifying losses or gains related to different human actions, such as land use and cover changes and biomass harvesting.

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