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Article

Estimación de parámetros forestales mediante datos de *Sentinel* 2A en Pueblo Nuevo, Durango

Estimation of forest parameters using Sentinel 2A data in *Pueblo Nuevo*, state of *Durango*

Pablito Marcelo López Serrano[1], Daniel José Vega Nieva[2], Hugo Ramírez Aldaba[2], Emily García Montiel[2*], José Javier Corral Rivas[2]

Resumen

Los bosques templados requieren de un monitoreo periódico con el fin de lograr un manejo sustentable. Los sensores remotos permiten hacer estimaciones de manera indirecta bajo el supuesto de que existe una correlación estadística entre datos satelitales y parámetros forestales. El objetivo del presente trabajo fue estimar el área basal (*G*), el volumen forestal (*Vta*) y la biomasa forestal aérea (*W*) mediante datos espectrales del satélite *Sentinel* 2A en la Comunidad de San Bernardino de Milpillas Chico, Pueblo Nuevo, Durango. Se realizó un análisis de correlación entre información dasométrica procedente de 22 Sitios Permanentes de Investigación Forestal y de Suelos (SPIFyS) e información espectral de alta resolución del sensor *Sentinel* 2A. Posteriormente, se generó un modelo de regresión múltiple para cada parámetro forestal. El coeficiente de correlación (*r*) más alto se observó en el NDVI con valores de 0.77, 0.68 y 0.76 para los parámetros forestales de *Vta*, *G* y *W*, respectivamente. Los modelos desarrollados explicaron 59 % de la varianza total observada en el *Vta* (*RCME*=57.60 m^3 ha^{-1}), 58 % en *W* (*RCME*=39.29 Mg ha^{-1}), y 51 % en *G* (*RCME*=4.40 m^2 ha^{-1}). El NDVI fue la principal variable predictiva en los tres modelos. Los datos de *Sentinel* 2A con resolución de 10 m en combinación con información dasométrica derivada de SPIFyS mostraron una buena capacidad para el mapeo de parámetros forestales en bosques templados.

Palabras clave: Área basal, biomasa aérea, parcelas permanentes, sensores remotos, *Sentinel*, volumen forestal.

Abstract

The temperate forests demand periodic monitoring in order to reach a sustainable management. The remote sensing makes it possible to indirectly generate estimates under the assumption of a statistical correlation between satellite data and forest parameters. The aim of this work was to estimate the basimetric area (*G*), the forest volume (*Vta*) and the aboveground biomass (*W*), using spectral data from the Sentinel 2A satellite in the *San Bernardino de Milpillas Chico* Community, *Pueblo Nuevo,* state of *Durango.* A correlation analysis was performed between mensuration information from 22 permanent plots for forest and soil research (SPIFyS) and high-resolution spectral information from the Sentinel 2A sensor. Subsequently, a multiple regression model was developed for each forest stand parameter. The highest correlation coefficient (*r*) was observed in the NDVI with values of 0.77, 0.68 and 0.76 for the forest parameters of *Vta*, *G* and *W*, respectively. The developed models explained 59 % of the total variance observed for *Vta* (*RCME* = m^3 ha^{-1}), 58 % for *W* (*RCME* = 39.29 Mg ha^{-1}) and 51% for *G* (*RCME* = 4.40 m^2 ha^{-1}). The NDVI was the main predictive variable in three models. The Sentinel 2A data with a resolution of 10 m in combination with mensuration information from SPIFyS showed a good capacity for mapping forest stand parameters in temperate forests.

Key words: Basimetric area, aboveground biomass, permanent plots, remote sensing, Sentinel, forest volume.

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[1]Universidad Juárez del Estado de Durango. Instituto de Silvicultura e Industria de la Madera. México.
[2]Universidad Juárez del Estado de Durango. Facultad de Ciencias Forestales. México.

*Autor para correspondencia; correo-e: e_garcia@ujed.mx

Introduction

The temperate forests of the state of *Durango,* Mexico, are the main source of wood production at the national level (SRNyMA, 2016). According to Segura and Trincado (2003), keeping the forests in use and in a sustained manner requires updated and reliable information about their natural resources. Therefore, it is necessary to carry out periodic monitoring of these ecosystems (Tomppo *et al.,* 2010). In this sense, the study of mensuration variables for forestry research allows following the dynamics and structure of the forest ecosystem (Gadow *et al.,* 2012; Hernández-Ramos *et al*., 2020). One way to do this is through permanent sites that represent an important basis for obtaining data on the effect of forestry on the growth, production and evolution of forest stands in short periods (Gadow *et al.,* 1999). However, this activity generally leads to long waiting times and high costs for the establishment of trees and the collection of information (Emborg, 1998; Toledo *et al.,* 2011).

The application of geospatial technologies is increasingly relevant to estimate and monitor forest parameters in short periods (Foody *et al*., 2003; Hall *et al*., 2006; Fuchs *et al*., 2009; Verbesselt *et al.,* 2010; Sobrino *et al.*, 2019). According to Herold *et al.* (2011) there is a particular interest in forest management in the use of remote sensors for the estimation of forest attributes, since they favor the obtaining of consistent, updated and spatially explicit data in areas of difficult access and with wide coverage. In this sense, the estimation of forest parameters from the combination of the use of remote sensors and georeferenced field sites (permanent sites) have become useful and reliable techniques for estimating variables such as forest volume, basimetric area and aboveground forest biomass (Hernández-Ramos *et al*., 2020; López-Serrano *et al*., 2020).

Through these technologies, such activity is carried out indirectly with the use of robust statistical techniques under the assumption of a high correlation between satellite data and data from the traditional inventory (Aguirre-Salado *et al*., 2011; Song, 2013; Wulder *et al.*, 2014; Acosta *et al.,* 2017; López-Serrano *et al*., 2020).

On the other hand, the availability and improvement of the capacities of the different types of sensors offer the opportunity to develop analysis techniques that maximize the estimates of forest parameters, with accurate information that comes from permanent forest and soil research sites, since they strengthen the input of them through remote sensors (Gibbons and Chakraborti, 2003; Barajas, 2007; Karjalainen *et al*., 2012; Miranda-Aragón *et al.,* 2013; Asner and Mascaro, 2014).

Based on the above, the aim of this work consisted of estimating the basal area (*G*), the forest volume (*Vta*) and the aboveground forest biomass (*W*), using spectral data from the Sentinel 2A satellite in the *San Bernardino* Indigenous Community of *Milpillas Chico, Pueblo Nuevo*, *Durango*.

Materials and Methods

Study area

The study area is located in the Indigenous Community of *San Bernardino de Milpillas Chico*, located in the *Pueblo Nuevo* municipality, *Durango,* Mexico (Figure 1). The Community has an area of 156 618.33 ha, where there are warm subhumid (Cw) and warm semi-cold climates [C(E)x]; the average temperature of the coldest month is 3 °C to 18 °C and the hottest month is 6.5 °C to 22 °C, with an average annual rainfall of 1 300 mm. The types of soil in the *Ejido* are: Regosol, Fluvisol and Cambisol, shallow and rocky. Its altitudinal range is from 2 500 to 2 600 m (Inegi, 2017b). The type of vegetation corresponds to pine forest, where the dominant tree species are: *Pinus durangensis* Martínez, *Pinus teocote* Schltdl. & Cham., *Pinus leiphylla* Schltdl. & Cham. and *Pinus cooperi* C.E. Blanco var. *cooperi* (Inegi, 2017a).

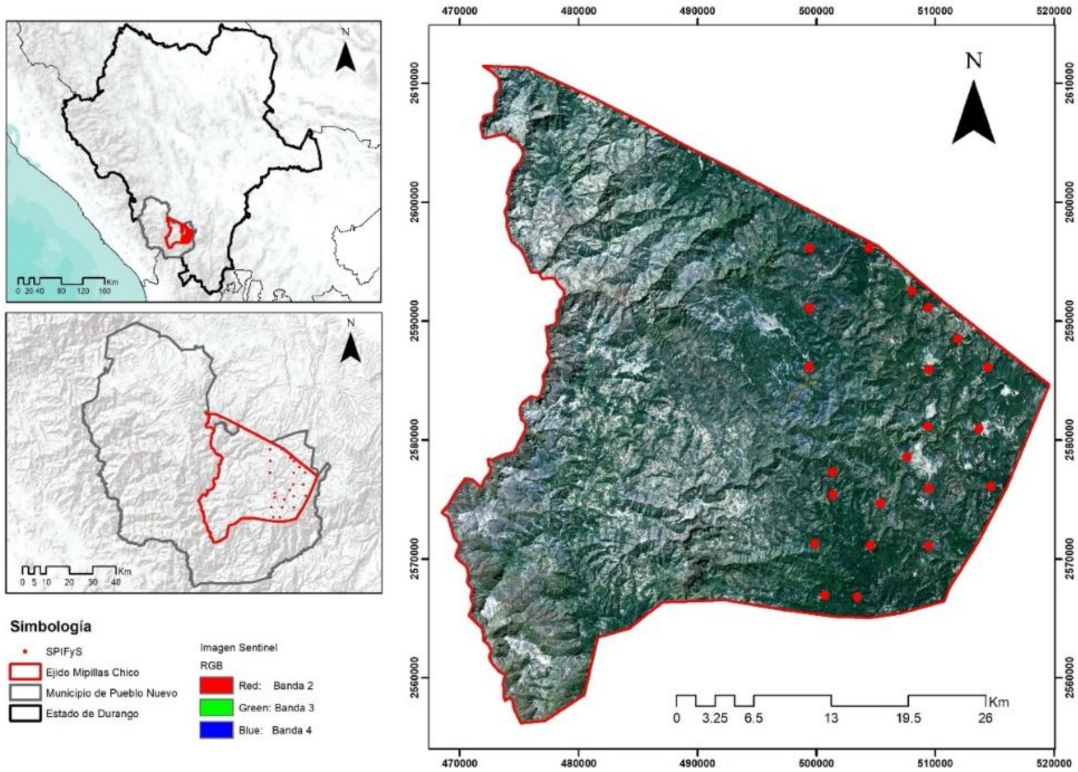


Figure 1. Location of the study area.

Field data

The dasometric data were obtained from 22 Permanent Forest and Soil Research Sites (SPIFyS, for its acronym in Spanish) established during the winter of 2009 using the methodology developed by Corral-Rivas *et al*. (2009), and subsequently measured at 5-year intervals (2014 and 2019). The SPIFyS measure 50 × 50 m and were located by systematic sampling with an average distance of 3 to 5 km between them. To calculate the basal area (*G*), the forest modeling techniques described by Diéguez-Aranda *et al*. (2005). Volume (*Vta*) and biomass (*W*) were estimated with the species-specific equations made by Simental-Cano *et al.* (2017) and Vargas-Larreta *et al.* (2017), respectively.

Acquisition and processing of satellite images

Three satellite scenes from the Sentinel-2A sensor (Table 1) were acquired and processed from the United States Geological Survey server (USGS-https: //glovis.usgs.gov). These images have a level 1 processing (Level 1C), of which only the visible and infrared sector bands were used, with the same spatial resolution (Table 2). In order to eliminate the effects of the atmosphere, the images were processed to obtain surface reflectance values (SR-Level 2A) using the Sen2Cor tool (Casella *et al*., 2018) in the Sentinel 2A Application Platform Software (SNAP) (Louis *et al*., 2016). Subsequently, the Normalized Difference Vegetation Index (NDVI) was calculated, in order to contribute to the estimation of forest parameters.

$$NDVI = (NIR - R) / (NIR + R)$$

Where:

NIR = Spectral band in the near infrared region

R = Band in the red region

Table 1. Characteristics of the images form the Sentinel 2A sensor used in this study.

Identificator	Aquisition date	Cloud cover (%)	Agency
T13QDF	22/11/2019	0.02	ESA
T13QEF	22/11/2019	0	ESA
T13QDG	22/11/2019	4.2	ESA

ESA = European Space Agency.

Table 2. Characteristics of the bands form the Sentinel 2A sensor used in this study.

Band	Wavelength (μm)	Resolution (m)	Abreviation
Blue	0.45 - 0.52	10	B1
Green	0.54 - 0.57	10	B2
Red	0.65 - 0.68	10	B3
Near infrared	0.78 - 0.90	10	IRC

Statistical analysis

A correlation analysis was carried out in order to find the relationship between spectral variables and forest parameters. Subsequently, multiple linear regression models were adjusted to identify the variables that best predict the forest parameters through the stepwise procedure (selection by steps), under the mixed strategy; that is, a combination of the forward and backward selection was used, through the MASS library (Ripley, 2020), in the R Core Team (2020) software.

The model used was of the form:

$$y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_n X_n + \varepsilon_j$$

Where:

y = Forest parameter to be estimated

X_n = Spectral bands and vegetation index

β_n = Regression coefficients

ε_i = Random error

G, *Vta* and *W* = Dependent variables

B1, *B2*, *B3* bands, *ICR* and *NDVI* = Independent variables

To evaluate the fit capacity of the model, the coefficients of goodness of fit, adjusted coefficient of determination were calculated. (R^2_{Adj}) as well as the root of the mean square of the error (*RCME*).

$$R^2{}_{Adj} = 1 - \left[\frac{n - 1 \sum_{i=1}^{n} (y_i - \mathrm{y}_i)^2}{n - \mathrm{p} - 1 \sum_{i=1}^{n} (y_i - \bar{y})^2}\right] \quad (1)$$

$$RCME = \sqrt{\left[\frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{n - p}\right]} \quad (2)$$

Where:

y_i = Observed value of the studied dependent variable

$\hat{y}_i$ = Predicted values of de studied dependent variable

$\overline{y}_i$ = Mean of the studied dependent variable

n = Number of total observations

p = Number of parameters of the model

Once the best model was assessed, it was used to generate the maps of each forest parameter, considering only the temperate forest area for the study area based on the use of soil and vegetation (INEGI, 2017a); This process was carried out using the raster library (Hijmans, 2020). Subsequently, the spatial distribution of the model error (residuals) of each parameter was generated by means of an Inverse Distance Weighted (IDW) interpolation, through the Gstat library (Pebesma, 2004). These processes were done in the R software (R Core Team, 2020). Figure 2 shows the work flow diagram of this study.

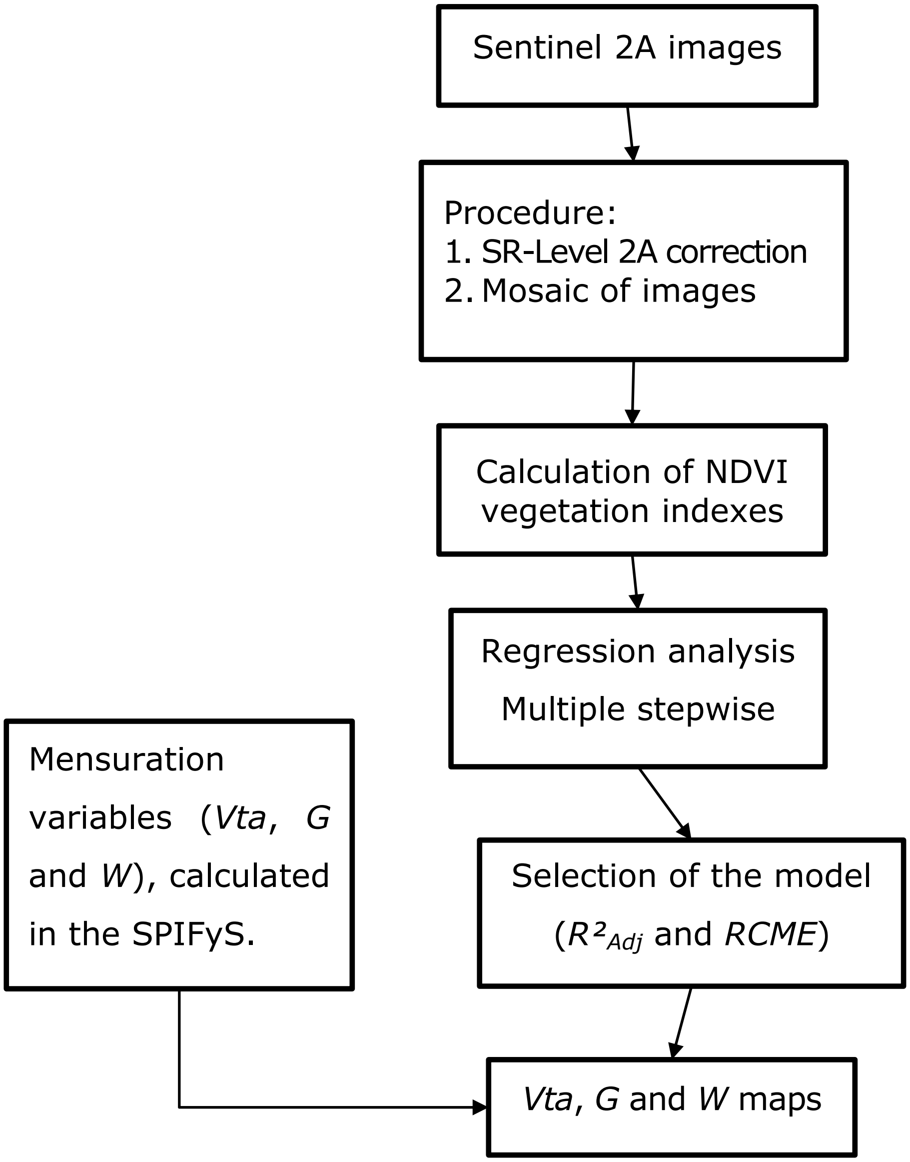


Figure 2. Work flow diagram of this study.

Results and Discussion

The main descriptive statistics for the dasometric variables per hectare in the study sites are summarized in Table 3. Results show that, in the Community of *San Bernardino de Milpillas Chico*, the basimetric area per hectare (*G*) is distributed in a 11.23 to 34.98 m^2 ha^{-1} range, with an average value of 19.82 m^2 ha^{-1}. *Vta* and *W* had 97.38 to 418.62 m^3 ha^{-1}, and from 54.271 to 289.418 Mg ha^{-1} values, with 198.037 m^3 ha^{-1} and 121.683 Mg ha^{-1} average, respectively. These results were similar to those obtained by Graciano-Ávila (2019) and López-Serrano (2020), for this type of forests in the region of the same municipality, *Pueblo Nuevo, Durango, Mexico*.

Table 3. Descriptive statistics of the forestry parameters estimated in the 22 SPIFyS.

Variable	Minimum	Maximum	Mean	*StD*
G	11.23	34.98	19.82	6.63
Vta	97.38	418.62	198.04	97.22
W	54.271	289.42	121.68	65.52

G = Basimetric area (m^2 ha^{-1}); *Vta* = Forest volume (m^3 ha^{-1}); *W* = Aboveground forest biomass (Mg ha^{-1}); *StD* = Standard deviation

The correlation between *G*, *Vta* and *W* of each SPIFyS with the different spectral bands and NDVI are shown in Figure 3. Pearson's correlation coefficient (*r*) ranged from -0.26 to 0.77. The analysis revealed a negative association in the reflectances of the B1, B2 and B3 spectral bands with the forest parameters, while the IRC and the NDVI had positive trends. The highest *r* value was presented in the NDVI of 0.68, 0.77 and 0.76 for *G*, *Vta* and *W*, respectively. This behavior is similar to that published by various authors under the same objective of estimating mensuration variables with several types of sensors in different forest masses (López-Serrano *et al.,* 2016; Acosta *et al*., 2017; Dos *et al.,* 2018; Hernández-Ramos *et al*., 2020).

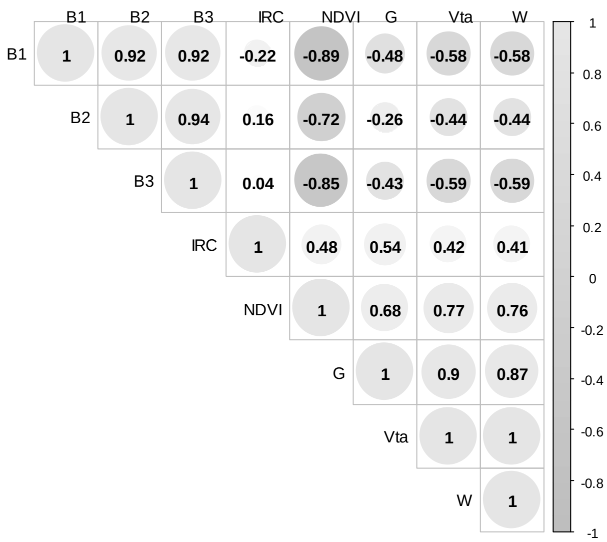


Figure 3. Pearson's correlation coefficients between spectral variables and forest parameters.

The high correlation observed in the NDVI (*r* => 0.60) with each of the dependent variables is due to the fact that this index has the ability to explain the variation in photosynthetically active vegetation given the combination of reflectance in the green and infrared spectrum of the electromagnetic sector (Chuvieco, 2002; Lu *et al.,* 2004). This makes it the most widely used vegetation index as a predictor in the estimation of forest biophysical parameters in the increasing accessibility of spectral information with increasingly fine spatial resolutions (Assmann *et al*., 2020; Myers-Smith *et al*., 2020).

The values of the adjusted coefficients of determination (R^2_{Adj}) and errors of the best models (*RCME*) to estimate the forest parameters in the study area are shown in Table 4. Figure 4 illustrates the distribution of the residuals of each one of the models. The R^2_{Adj} statistic of the regression models estimated in the present study ranged from 0.51 to 0.59. In the estimation of *Vta*, the value of R^2_{Adj} was slightly higher, since the model managed to explain 59 % of the total variance observed in this attribute (*RCME* = 57.60 m^3 ha^{-1}). The value of this statistic is slightly lower than that obtained by Chrysafis *et al.* (2017), who estimated the forest volume in Mediterranean forest ecosystems, and were based on Sentinel-2 images, although in their case they calculated an error greater than that estimated in this work (R^2 = 0.63; *RCME* = 63.11 m^3 ha^{-1}) and Landsat 8 OLI (R^2 = 0.62; *RCME* = 64.40 m^3 ha^{-1}) and higher *RCME*.

Table 4. Regression models used in this study with their respective adjustment statistics.

Model	***β***	**Value**	R^2_{Adj}	***RCME***
$G = \beta_0 + \beta_1 B2 + \beta_2 NDVI$	β_0	-33.096	0.51	4.4
	β_1	0.03543		
	β_2	65.5993		
$Vta = \beta_0 \beta_1 B3 + \beta_2 ICR + \beta_3 NDVI$	β_0	-1 478.4	0.59	57.6
	β_1	1.4387		
	β_2	-0.3673		
	β_3	2 801.5		
$W = \beta_0 + \beta_1 B3 + \beta_2 ICR + \beta_3 NDVI$	β_0	-1 021.2	0.58	39.29
	β_1	0.9901		
	β_2	-0.2546		
	β_3	1 915.4		

G = Basimetric area (m^2 ha^{-1}); *Vta* = Forest volume (m^3 ha^{-1}); *W* = Forestal biomass (Mg ha^{-1}); *β* = Parameters of the model; R^2_{Adj} = Adjusted coefficient of determination; *RCME* = Root of the mean square of the error.

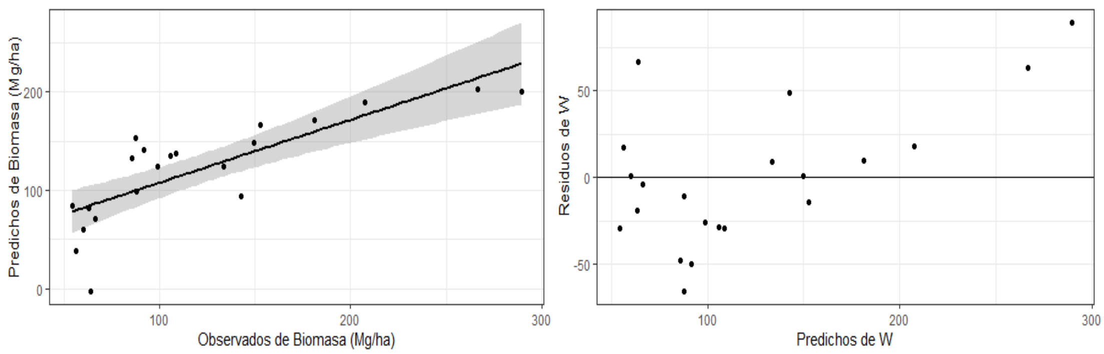


Figure 4. Predicted values *versus* observed values of the selected models for the estimation of the studied forest parameters.

On the other hand, Hu *et al.* (2020) estimated the forest volume through a multiple linear regression analysis (R^2 = 0.49; *RCME* = 70.22 m^3 ha^{-1}), based on the variables derived from Sentinel-2, in the forests of the province of Hunan, China.

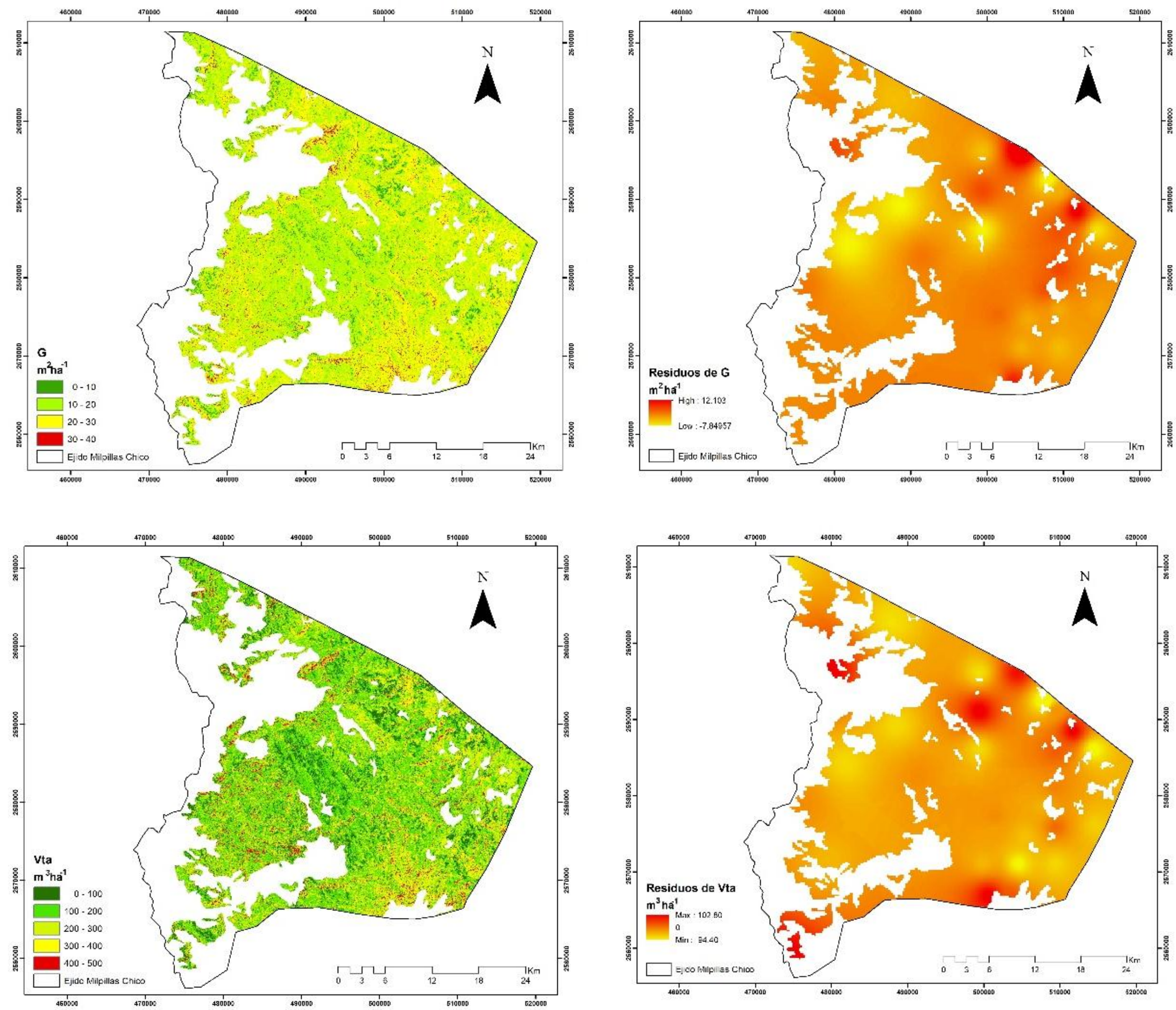
Particularly in Mexico, these results were above those of Hernández-Ramos *et al*. (2020), who estimated the volume (R^2_{Adj} = 0.32; *RCME* = 68.39 m^3 ha^{-1}), the basimetric area (R^2_{Adj} = 0.28; *RCME* = 7.64 m^2 ha^{-1}) and biomass (R^2_{Adj} = 0.32; RCME = 3 5.65 Mg ha^{-1}), under a multiple linear regression statistical technique, in different forest ecosystems by combining medium resolution spectral information (Landsat) and information derived from the National Forest and Soil Inventory (INFyS) in the state of *Quintana Roo*.

On the other hand, Torres-Vivar *et al.* (2017) calculated the *Vta* (R^2_{Adj} = 0.66; *RCME* = 62.3 m^3 ha^{-1}), *G* (R^2_{Adj} = 0.66; *RCME* = 5.82 m^2 ha^{-1}) and *W* (R^2_{Adj} = 0.66; *RCME* = 32 Mg ha^{-1}) in coniferous forests in the state of *Hidalgo*, by means of a multiple regression analysis and data from the high-resolution sensor SPOT 6. Under the same scheme, in low-deciduous forest ecosystems and with medium-resolution data (Landsat) in the State of Mexico, Acosta *et al*. (2017), determined *RCME* values for *Vta* of 13.18 m^3 ha^{-1} (R^2_{Adj} = 0.66), while for *G* a value of 3.30 m^2

ha^{-1} (R^2_{Adj} = 0.52) and finally for *W* 5.91 Mg ha^{-1} (R^2_{Adj} = 0.60), these figures were higher than those of the present work.

Such variation in the results of the *RCME* and R^2_{Adj} in the estimation and monitoring of the vegetation with remote sensors could be attributed to the spatial resolution of the images, the environmental conditions in which they were acquired, and even the type of vegetation in each case study (López-Serrano *et al.,* 2016; Torres-Rojas *et al*., 2016; Hawryło *et al.,* 2018; Pham *et al.,* 2019; Hernández-Ramos *et al*., 2020; López-Serrano *et al.,* 2020).

Finally, once the best model had been selected, the maps were generated for each forest parameter studied and the spatial distribution of the error of said model was plotted (Figure 5). In *G*, the spatial distribution in the study area varied from 0 to 40 m^2 ha^{-1}, for *Vta* from 0 to 500 m^3 ha^{-1} and *W* from 0 to 300 Mg ha^{-1}. These maps represent a diagram of the distribution of the forest resource, which can be integrated into the forest management plan to improve it.



G
m2ha-1
0 - 10
10 - 20
20 - 30
30 - 40
Ejido Milpillas Chico
N
Km
Residuos de G
m2ha-1
High : 12.103
Low : -7.84957
Ejido Milpillas Chico
Vta
m3ha-1
0 - 100
100 - 200
200 - 300
300 - 400
400 - 500
Ejido Milpillas Chico
Residuos de Vta
m3ha-1
Max : 102.60
0
Min : 94.40
Ejido Milpillas Chico

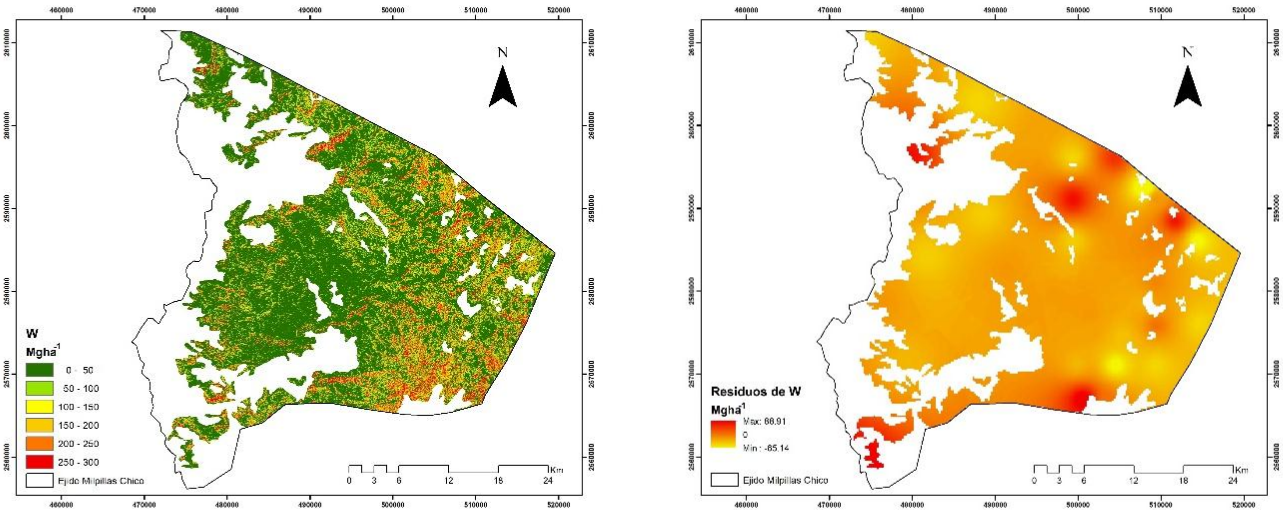


Figure 5. Spatial estimation and spatial distribution of the error of *G*, *Vta* and *W* in the forests of the *San Bernardino de Milpillas Chico* Indigenous Community.

Conclusions

The generation of regression models made it possible to indirectly estimate *G*, *Vta* and *W* using spectral information derived from the Sentinel 2A sensor and mensuration data from SPIFyS. The NDVI vegetation index was the spectral variable that presented the highest correlation with the studied forest parameters (0.68-0.77). The high resolution images from the Sentinel 2A sensor proved to be a useful tool for mapping forest parameters in temperate forests at the regional level.

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Conflict of interests

The authors declare no conflict of interests.

Contribution by author

Pablito Marcelo López Serrano: statistical analysis and writing of the manuscript; Daniel José Vega Nieva: review and correction of the manuscript; Hugo Ramírez Aldaba and Emily García Montiel: review and coordination of the editing process; José Javier Corral Rivas: field sampling, methodology design and review of the manuscript.

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