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Influence of spatial resolution on fuelwood supply estimations

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Abstract

In this study we analyze how the spatial resolution of three satellite images affects estimates of fuelwood availability in a region located in Southern India. For this purpose, we rely on satellite imagery, ground-truthing through GNSS Data Logger, and data from productivity value records. Preliminary findings suggest that higher-resolution satellite imagery significantly improves the accuracy of fuelwood source estimations, revealing a complex mosaic of available biomass often overlooked by coarser map scales of analysis. By incorporating localized data on fuelwood collection patterns and the spatial distribution of biomass, we aim to enhance predictive models that can more accurately forecast fuelwood availability. In didactic terms, we consider this analysis to be a good example that provides a comprehensive understanding of how the characteristics of satellite imagery can influence the cartographic products that are the basis for decision making. It also has significant potential to be utilized online as a practical exercise in GIS and remote sensing courses, allowing students to practically analyze a real-world case, thereby enhancing meaningful learning.

Keywords: Satellite Imagery, Spatial Resolution, Map Scale, Wood Energy, India, Teaching Geography

1. Introduction

One major flaw in the so-called fuelwood gap theory of the 70s' (Eckholm, 1975) was an underestimation of woody biomass resources, mainly because non-forests biomass and the vegetation's response to collection and harvesting strategies were not considered in global and regional estimates[1] (Pandey, 2002; Bensel, 2008; Rüger et al., 2008; He et al., 2009; Jagger and Shively, 2014).

Since decades now it is known that wood for cooking and heating comes from virtually everywhere in the landscape, such as forests, woodlands, agroforestry systems, wastelands, scattered trees in agricultural areas or on the edges of roads, and family orchards; but also from within urban environments, industrial facilities producing biomass residues, and even along the shores of water bodies (RWEDP, 1997; Pandey, 2002; Rüger et al., 2008).

From a remote sensing perspective aimed at mapping fuelwood availability across broad areas, all these fuelwood sources are highly diverse in terms of spatial extent, texture, and patchiness. In consequence, both the spatial resolution (size of each pixel on the ground) and the classification method should influence how accurately fuelwood sources can be mapped. While sub-meter resolution imagery can in principle detect very small sources (e.g. a few bushes by a river), it presents many technical challenges when covering large areas such as entire countries. A question not yet resolved arise: How to balance between mapping large areas while accounting for pulverized fuelwood sources not detectable by medium to low resolution sensors. In other words, how sensitive are supply-demand estimations to fuelwood supply maps produced at varying spatial resolutions?

Previous studies have analyzed how spatial resolution can influence estimates of woody canopy cover and deforestation and forest degradation (D&D) (Ponzoni et al., 2002; de Wasseige and Defourny, 2004; Asner et al., 2005; Harris et al., 2012; Souza et al., 2013; Fisher et al., 2017; Shafeian et al., 2021). Furthermore, a few studies ntion fuelwood extraction and its potential relationship with D&D, but they all fall short on explicitly addressing the question of how spatial resolution could eventually tilt supply estimations significantly (Pandey, 2002; Shafeian et al., 2021).

In this study, we estimated fuelwood supplies within a 24,779 ha area in central Karnataka, India by means of visual interpretation of satellite imagery at three different resolutions, with and without counting Trees Outside Forest (TOFs); and later related woody area with biomass stocks from the literature. We used georeferenced tracks from a sample of fuelwood collectors in three villages to validate the actual Land Use and Land Cover (LULC) class people were visiting for collecting fuelwood during a three-month survey conducted from December 2013 to April 2014.

In addition to the above, this work has a second objective: to make new contributions to the field of situated learning in geography and GIS with proposals that promote active knowledge and practical application of theoretical concepts (sensu Ridha et al., 2020). In this sense, this work is a new experience in the field of photointerpretation with satellite images, a useful tool both for geographic analysis (spatiotemporal dynamics, natural risk analysis, climate change) and for the generation of thematic maps (land cover and uses, geomorphology, geology, landscape) (Lillesand et al., 2015).

Aerial photointerpretation is an essential exercise in geography programs at the university level. This study is designed to be effectively implemented as a practical exercise within the context of GIS or Remote Sensing topics, seeking the acquisition of analytical skills, practical and applied learning, and the development of relevant technological competencies in the professional field (sensu Sinton, 2009; Schulze et al., 2013).

2. Material and methods

2.1 Study area

The study area is a rectangular cutout of 24,778 ha located between the coordinates 15° 37’ 54.66’’N, 76° 16’ 08.53’’E and 15° 31’ 25.40’’N, 76° 27’ 48.88’’E within Koppal

[1] Wood can be considered a conditionally renewable resource because trees grow naturally in many environmental conditions. If wood is harvested at or below the rate at which it naturally regenerates, then harvesting is sustainable. However, if more wood is harvested than the landscape can replace, as is often the case in low- and middle-income countries (where people rely heavily on fuelwood and charcoal), harvesting is not sustainable and tree cover will decline over time. This causes landscape degradation and may also contribute to long-term deforestation.

district, in the state of Karnataka in southern India (Figure 1). The average altitude is about 470 MSL, the climate is semi-arid with a warm summer, an annual precipitation of 571 mm, and maximum and minimum temperatures of 45 °C and 16 °C, respectively.

The topography is moderately flat among shallow valleys and granitic hills positioned along a northeast-southeast line and hosting a variety of shrubs usually collected as fuelwood. Koppal's main waterbody is the Tugabhadra River, a tributary of the Krishna River along its right banks, corresponding to the basin of the same name (GWIB, 2008; Government of India, 2011).

The area was chosen because is a good representation of places that are classified as fuelwood *hot spots* (i.e. deficit areas) because they host a large and relatively dense population using fuelwood, over a highly fragmented landscape with most fuelwood sources represented by scattered trees and shrubs difficult to detect by moderate and low spatial resolution satellite images; which are frequently used in country-wide/national level assessments (Ramachandra, 2010; Drigo et al., 2014; Bailis et al., 2015).

The main supply source of fuelwood comes from thorny shrubs, which are characteristic of arid or semi-arid climates (FCN, 2012), where the predominant species is *Prosopis juliflora*, a shrub that, because it is highly adaptable to arid environments, has come to be considered an invasive species (Walter and Armstrong, 2014; Edrisi et al., 2020).

It is known locally as *Bellary jali*, and it was introduced in India in the past century as part of a strategy to reforest and combat soil erosion. This tree grows quickly, is tolerant of salt and drought, and – because it adapts easily to dry climates –is considered to be a weed because it spreads rapidly, mainly in pasture land, crop areas, and along river banks (Shanwad et al., 2015). Although it is attributed with different negative impacts on native biodiversity, it is also widely used to restore degraded areas in addition to having high potential as fuelwood, charcoal, wood and syrup due to its high calorific value (Oduor and Githiomi, 2013; Walter and Armstrong, 2014; Shanwad et al., 2015).

2.2 Satellite image acquisition and interpretation of land use maps at different geographical scales

Free images with geometric corrections were downloaded from the remote Landsat and Sentinel-2 sensors, offering resolutions of 30 meters and 10 meters, respectively.

A four-band composition was used for these sensors (table 1), allowing for the creation of false-color composites to highlight distinctive features of land cover and use. The selection of different scenes was based on visual quality, with less than 10% cloud cover and falling within the appropriate seasonal range. Additionally, a high-resolution image with a 30 cm resolution was downloaded from the SAS PLANET[2].

The high-resolution capability of this image was sufficient to visually detect (at a detailed spatial scale[3]) different geographic features such as buildings, trees, water bodies, etc., and easily perform on-screen digitizing in GIS to prepare the land use map.

The map scales chosen for photointerpreting the LULC were defined based on the spatial resolution potential of each image, as shown in Table 1. The interpretation scales were 1:60,000 for Landsat and 1:20,000 for Sentinel.

The Google earth image enabled mapping at a scale of 1:5,000 and estimating scattered trees in agricultural areas at a scale of 1:1,000 (see section 2.4 Trees Outside Forests).

The method used to photo interpret the images was, the Food and Agriculture Organization, visual interpretation method was applied (FAO, 1996). Meanwhile, applying the photo interpretation method requires assigning a minimum mapping unit (MMU) that helps provide coherence to the cartography, which is why we applied the one suggested by Priego and Bocco (2011) (4 X 4 mm) because it guarantees the cartographic functionality and the correct reading of the map (Franch-Pardo et al., 2017).

[2] Software that allows users to view and download high-resolution satellite photos.

[3] When we mention the scale we refer to the measure of the amount of reduction that a mapped feature has with respect to its real counterpart on the ground.

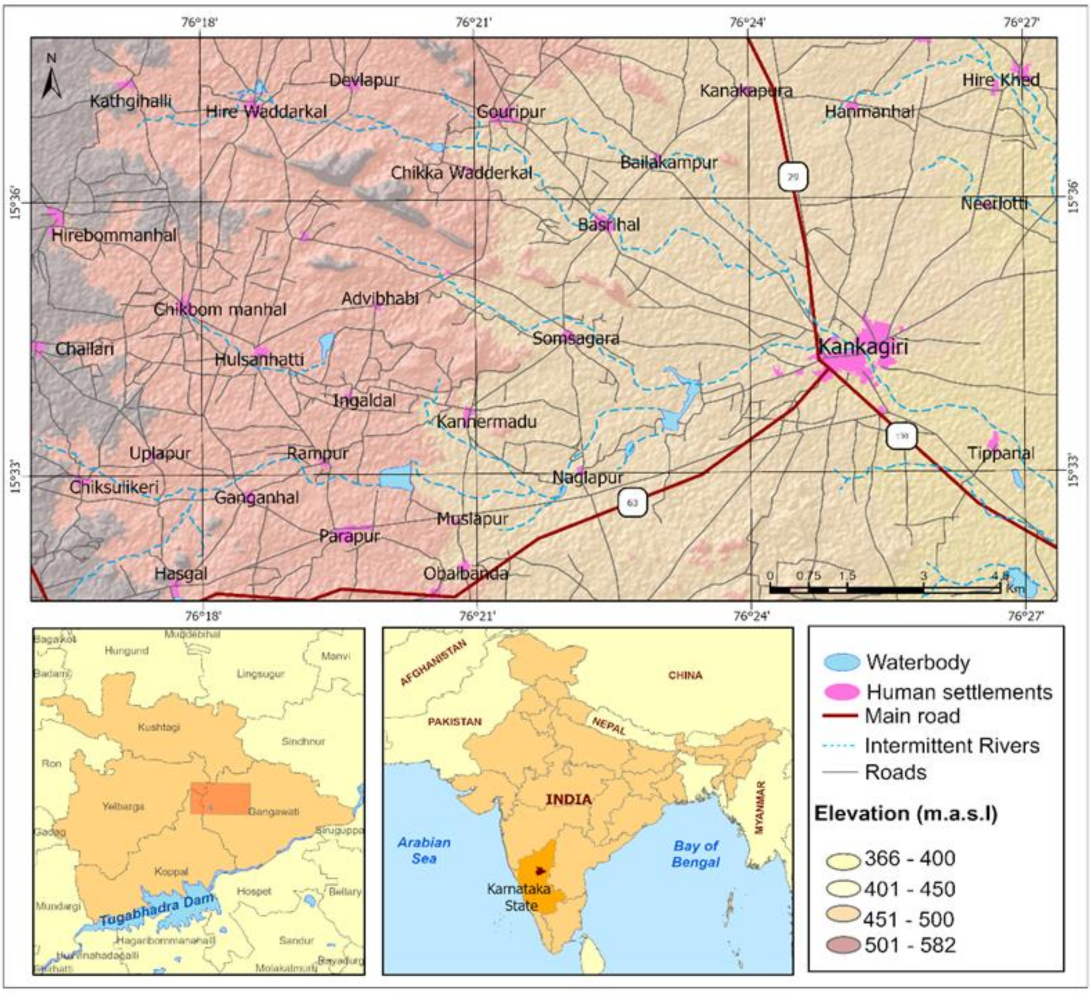

Figure 1. Study area in Koppal district, Karnataka, India. Authors' elaboration.

Data type	Image date	Spatial resolution	Composite imagery	Interpretation scales
The Operational Land Imager (OLI) and the Thermal Infrared Sensor (TIRS)1	June 2016	30 m	Multiespectral image (Infrared color)	1:60000
Sentinel-2[2]	December 2015	10 m	Multiespectral image (Infrared color)	1:20000
Google Earth [3]	April 2016	30 cm	Espectral image (Natural color)	5000
				1000

1 The bands used for photointerpretation in Landsat were B2 (Blue) B3 (Green), B4 (Red) and B5 (Near infrared)

2 The spatial resolution of spectral bands of the Sentinel -2 sensor is 20 m and 10 m. For the interpretation, only the 10-meter B2 (Blue), B3 (Green), B4 (Red) and B8 (Visible and near infrared) bands were used.

3 The high resolution image in natural color was downloaded from Google Earth with the SAS PLANET application and was used to make two photointerpretations at different scales. (see methods section: quantification of trees outside of forest).

Table 1. Data from the satellite images used for this study. Authors' elaboration.

2.3 Reliability analysis of the land cover cartography

To assess the quality of the classification, a confusion matrix was developed, consisting of a two-dimensional table that allows for assessing the quality of each category by calculating errors of omission and commission (Salvador et al., 1996).

The rows show the “true-terrain” reference values while the columns display the values obtained from the classification. The errors to be identified are of omission or commission, and the Kappa index (KI) was applied to assess the classification’s precision (concordance), which accounts for the contribution of chance in the map’s reliability (Mas et al., 2003).

a) Sampling

The thematic map’s reliability analysis consisted of assessing the projected information on the cartography, which was contrasted with other, more reliable information sources. Overall, it is based on a sampling of verification sites that are classified based on field observations or by analyzing satellite images with higher resolution than those used to produce the map (Mas et al., 2003). A random stratified sample was taken, and 60 % of the polygons that comprise the LULC map selected for each category.

b) Validation of verification sites

The Landsat and Sentinel validation was done through an image with higher spatial resolution, while a more detailed a map scale was applied for Google earth image than the one used to develop the LULC map.

c) Confusion matrix

The confusion matrix allowed for identifying the omission and commission errors, where the former are the elements that do not appear in the category that they belong to because they were erroneously included in another one, while the commission errors are the elements that appear in a class that they do not belong to.

2.4 Estimation of trees outside forests

For this exercise, a grid with square modules of 1 hectare was designed, which was overlaid on the Google earth image (only the agricultural area was considered). Then, a random sampling was conducted on the grid to randomly select 130 cells. Within these cells, trees outside forests (TOFs) were identified and digitized. This process allowed for extrapolation to estimate the coverage of scattered trees in agricultural land use that were not detected in Landsat and Sentinel images.

2.5 GNSS Data Logger tracking of fuelwood collection sites for cross-validation

Between December 2013 and April 2014, 30 GNSS Data Logger[4] devices were distributed to residents of the Koppal district, specifically in the towns of Nerlotti, Upalapur, and Chikkawadrakal, who regularly collect fuelwood. These devices were paired with a custom-developed Android app designed to collect, process, contextualize, and analyze mobility patterns and time allocation. Voluntary participants carried the devices with them throughout their daily activities to help identify fuelwood harvest sites.

Every 3 to 5 days, the recorded tracks from the devices were uploaded to a widescreen tablet and displayed over a Google Maps satellite image. A brief multiple-choice interview was then conducted to identify what the person wearing the device was doing at various times and locations along the recorded track. Areas where participants engaged in activities, such as collecting firewood, grazing livestock, or working in the fields, were saved as polygons drawn on the screen by the interviewer. Depending on internet connectivity, the data was either stored on the tablet or sent to the cloud for remote analysis in near real-time. Spatial and temporal descriptive statistics of the tracks and participants’ activities were calculated automatically.

[4] Brand and model of devices: Columbus v990 GNSS trackers with point positioning.

Based on this monitoring, the information was processed using GIS, and the collection zones were spatially delineated in collaboration with the GNSS Data Logger users. This resulting data provided cross-validation between the collection zones identified in the field and the land use/land cover (LULC) maps.

2.6 Fuelwood availability

To estimate the availability of fuelwood in the area of study, documentary sources were reviewed, identifying the productivity values of the *Prossopis juliflora* species. Due to the scarcity of these types of data in the search, it was limited to India, while productivity data from other LULCs were taken from secondary sources from other parts of the world.

3. Results

3.1 Spatial analysis of land uses and land covers as a biomass source

In the Landsat image, eight categories of land uses and land covers were identified, while in the Sentinel 9 and Google earth images, ten classes were identified. These were the recorded categories: agriculture, human settlements, waterbodies, shrublands (dense and open), tree plantations (only in Landsat and Sentinel), riparian vegetation (dense and open), waterlogged areas, and stony waste (only in Sentinel).

In the area of study, agriculture is the most represented category, while the rest of the categories are minimally represented. The resolution allowed for establishing different nominal categories; that is, the number of classes varied depending on the resolution. In this case, Google earth image had greater detail, which resulted in a higher number of class (Table 2).

All the natural vegetation that is not associated with waterbodies and that is primarily located in sloped areas was classified as shrubland, whereas we identified riparian vegetation next to riverbanks and in low areas. Table 2 shows the surface in hectares along with the percentage of each of the categories identified in each sensor.

3.2 Reliability analysis of the land cover cartography

The Landsat sensor presented an overall reliability (OR) of 78.1 % (Table 3) and a Kappa index with a nearly perfect concordance of between 0.81 and 100 in the dense riparian vegetation, dense shrubland, human settlements, open riparian vegetation, and open shrubland. Substantial concordance of 0.7 was present in the waterbodies, while there was a moderate concordance of 0.60 in agriculture. Finally, there was an insignificant concordance of 0.25 in zones classified as waterlogged areas.

Figure 2 shows the LULC cartography of the study area on the left, which was developed based on the different sensors, while the resolution's influence on the fragmentation of the landscape is exemplified on the right through zoom-in windows. That is, as the resolution and scale increased, patches of vegetation emerged in agricultural areas.

In the cartography derived from the Sentinel sensor, the overall reliability was 88.5 % and the Kappa index indicated that nine of the ten categories had a concordance value within the range of 0.81-1.00, which means a nearly perfect concordance strength, while the category classified as open shrubland had a value of 0.60, that is, a moderate concordance.

In the Google earth image, the overall reliability was 96 %, and all the categories classified with this sensor had a concordance value within the 0.88-1.00 range.

In broad terms, this means that, of the three sensors used to classify the land uses and land covers, the Google earth image is more reliable and, although the results also depend on the classification method, the high resolution associated with the visual method makes it possible to identify different elements such as patches of trees outside the forest, which are often not perceived in other scales of analysis.

3.3 TOF estimate

The high spatial resolution of the SAS PLANET images enabled photointerpretation of certain areas at a 1:1,000 scale, allowing for the identification of scattered trees within the agricultural cover. The total surface of the scattered TOF in the sample area was 11.24 ha. Based on this data, an inference for all agricultural areas was made, in which a total of 1680 ha of shrubland was estimated, which had not been recorded or counted in other images with smaller resolutions.

The result of this exercise was applied to the LULC analysis on a map scale of 1:5,000, that is, 1680 ha were subtracted from the agricultural surface and this same value was added to the surface cataloged as dense shrubland.

Land covers	Landsat		Sentinel		Google Earth	
	Ha	%	Ha	%	Ha	%
Agriculture	20191	81.5	20268	81.8	17980	72.6
Human settlements	138	0.6	303	1.2	335	1.4
Waterbodies	76	0.3	106	0.4	18	0.1
Open shrubland	629	2.5	741	3.0	1374	5.5
Dense shrubland	861	3.5	990	4.0	2935	11.8
Forested plantations	n/a	n/a	153	0.6	289	1.2
Open riparian vegetation	1294	5.2	880	3.6	539	2.2
Dense riparian vegetation	692	2.8	946	3.8	1029	4.2
Waterlogged areas	897	3.6	392	1.6	248	1.0
Stony waste	n/a	n/a	n/a	n/a	30	0.1
Total	24779	100	24779	100	24779	100

Table 2. Classification of the land uses and land covers per sensor. Authors' elaboration.

Satellite imagery	No. Polygons totals	No. validated polygons (60 %)	Overall reliability (%)
Landsat	121	73	78.1
Sentinel	333	200	88.5
Google Earth	1963	1178	96

Table 3. Reliability of the LULC cartography. Authors' elaboration.

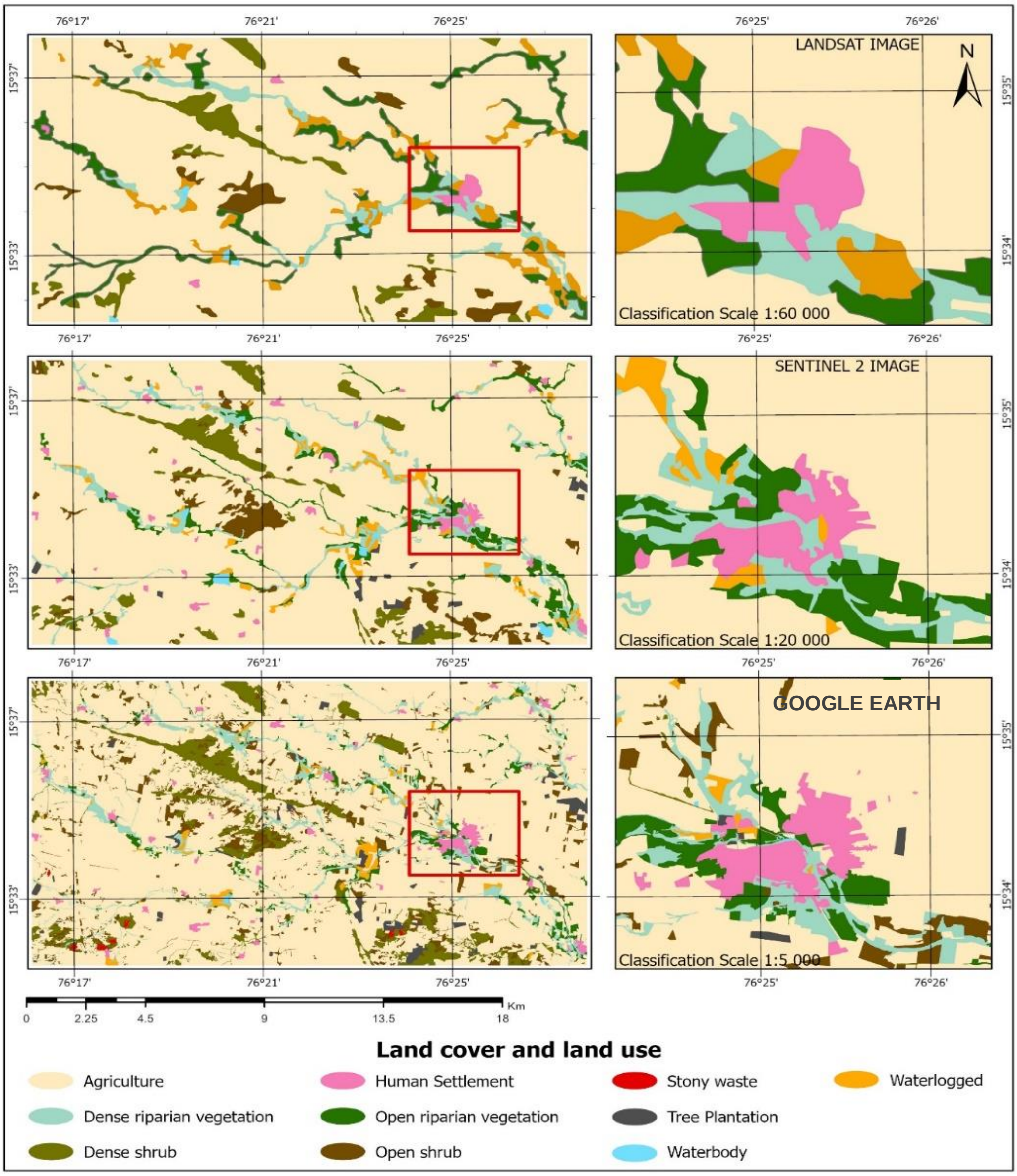

Figure 2. Maps of land covers produced through the visual interpretation of Landsat, Sentinel, and Google earth images. Authors' elaboration.

Image	Spatial resolution	A	AH	CA	VN	ZA	ZN	P	Collection sites
Landsat	30 m	170	0	0	71	0	0	0	241
Sentinel	10 m	159	2	0	80	0	0	0	241
Google Earth	30 cm	138	1	0	102	0	0	0	241

A= Agriculture; HS = Human settlements; WB= Waterbodies; NV= Natural vegetation (including shrubland and riparian vegetation); WA = Waterlogged areas; S = Stony waste; P= Tree plantations.

Table 4. Relation between collection zones and land use and land cover per sensor. Authors' elaboration.

AGB Stock (t ha-1)	Place	Author
1.40-27.69 t/ha	Tamil Nadu, India	(Saraswathi and Chandrasekaran, 2016)[1]
75.09-103 t/ha	Banthra, Lucknow India	(Goel and Behl, 1996)[2]
44.06 t /ha	Banthra, Lucknow India	(Goel and Behl, 2001)[3]

[1] Stands of 5–10-year-old trees, dry weight, measured in river ecosystems

[2] Stands of 5–10-year-old trees, dry weight

[3] Stands of 3.5-year-old trees, dry weight

Table 5. Relation between collection zones and land use and land cover per sensor. Authors' elaboration.

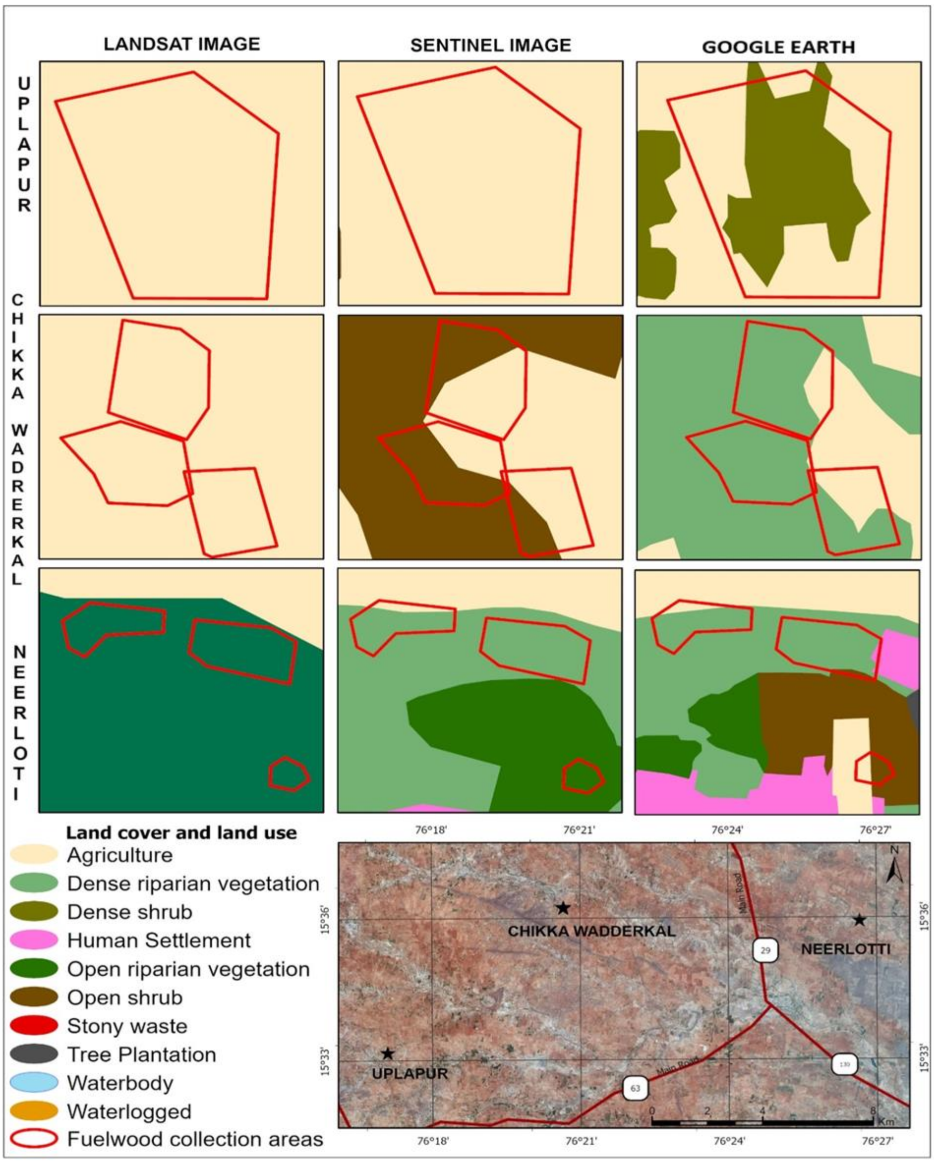

Figure 3. Collection zones based on GNSS Data Logger data and visual classification of satellite images. Authors' elaboration.

Land uses and land covers	AGB Stock (t/ha)	Source
Agriculture	0.8-1.0	(Ghilardi, et al., 2007)
Human settlements	0.2-0.4	(Ghilardi, et al., 2016)
Waterbodies	0.1-0.5	(Ghilardi, et al., 2016)
Open shrubland	22.0-51.5	(Saraswathi and Chandrasekaran, 2016)
Dense shrubland	44.1-103.3	(Saraswathi and Chandrasekaran, 2016)
Forested plantations	2.5-5.0	(Ramachandra, 2010 and Ramachandra et al., 2004)
Open riparian vegetation	2.8-13.8	(Goel and Behl, 1996)
Dense riparian vegetation	13.8-27.7	(Goel and Behl, 1996)
Waterlogged areas	0.4-0.8	(Ghilardi, et al., 2016)
Stony waste	0.2-0.4	(Ghilardi, et al., 2016)

Table 6. Maximum and minimum productivity values per LULC category. Authors' elaboration.

Categories	AGB Stock (t/ha)		Land covers surface in hectares			Fuelwood estimate					
						Landsat		Sentinel		Google Earth	
	MIN	MAX	Landsat	Sentinel	GeoEye	MIN	MAX	MIN	MAX	MIN	MAX
Agriculture	0.8	1.0	20191	20268	17980	16153	20191	16214	20268	14384	17980
Human settlements	0.2	0.4	138	303	335	28	55	61	121	67	134
Waterbodies	0.1	0.5	76	106	18	8	38	11	53	2	9
Open shrubland	22.0	51.5	629	741	1374	13857	32394	16324	38162	30269	70761
Dense shrubland	44.1	103.3	861	990	2935	37936	88941	43619	102267	129316	303186
Forested plantations	2.5	5.0	n/a	153	289	n/a	n/a	383	765	723	1445
Open riparian vegetation	1.4	2.5	1294	880	539	1812	3623	1232	2464	755	1509
Dense riparian vegetation	13.8	27.7	692	946	1029	9550	19168	13055	26204	14200	28503
Waterlogged areas	0.4	0.8	897	392	248	359	718	157	314	99	198
Stony waste	0.2	0.4	n/a	n/a	30	0	0	0	0	6	12
Total			**24,779**	**24,779**	**24,779**	**79,701**	**165,128**	**91,055**	**190,618**	**189,821**	**423,737**

Table 7. Aboveground biomass estimates by category. Authors' elaboration.

3.4 Monitoring of the fuelwood collection sites for cross validation based on GNSS Data Logger

Table 4 shows the result of the cross validation, where it is apparent that agriculture is the category that is most used to obtain fuelwood and that, as the spatial resolution increases, the number of sites in agricultural areas decreases.

This means that there are patches of natural vegetation or scattered trees within the agricultural plots that are used as a source of fuelwood and that are not captured on coarser geographical scales.

In the areas of natural vegetation that include shrubland and riparian vegetation, the opposite occurs.

Figure 3 exemplifies the cross-validation results through windows. On the right, it shows the name and location for each example (zoom), and the corresponding sensor is specified along the top. The red polygons represent extraction sites from different localities superimposed on each sensor's LULC results. As seen, there is variation from sensor to sensor.

The examples show that, as the spatial resolution increases, the LULC categories change and, therefore, the collection sites start to be associated with categories that have a greater presence of fuelwood (Fig. 3).

The values reported for the *Prosopis juliflora* species for India were highly variable, fluctuating between 1.4 and 103.32 t/ha (Table 5). The values reported in the three documents cited in table 5 were used for this study, which also correspond to case studies in which the biomass productivity of the *Prosopis juliflora* species was reported in t/ha.

3.5 Biomass estimate

a) Review of productivity data.

Considering the previous reports, minimum and maximum productivity ranges were established for natural vegetation. The data for quantifying the biomass in the categories that are not natural vegetation are even scarcer. Therefore, values reported in studies from other parts of the world were used. In many cases, these data have been approximations or they come from unpublished field data (Ghilardi et al., 2007).

Table 6 shows the minimum and maximum productivity values, both for natural vegetation and for the other categories identified in the study area.

b) Aboveground biomass (AGB) estimates in the area of study.

The fuelwood estimate calculated with data reported in the literature in relation to the LULC surfaces for each sensor can be seen in table 7.

The results indicated a variation, even when the calculation was done with the same sensor. Regardless of the productivity data used to estimate the supply, the effect of the input used has a considerable weight. In this case, the minimum and maximum estimates were more similar between the Landsat and Sentinel images, while there were higher values in the Google earth images (table 7).

4. Discussion

While there are various methods for classifying the LULCs, in terms of availability, an analysis with resolutions and geographical scales is needed that allows for identifying the scattered or low-density supply sources, such as those located in arid or semi-arid zones where it is complicated to distinguish them, even with high resolution.

We consider that studies based on photo and field interpretation with GNSS Data Logger are fundamental for technological advancements in matters of automatic LULC classification, and more matches will be achieved with these algorithms as more surfaces are covered with these techniques.

As mentioned, this aspect becomes even more present in arid regions, because they are robust and effective methods in areas whose dimensions are manageable with a reasonable workload.

While we know these methods have disadvantages in terms of the excessive time that can sometimes be invested in the classifications (Wang et al., 2008; Zanella et al., 2012) or the need to have prior knowledge of the area of study (Kumar et al., 2017), the geospatial sciences community needs these techniques, which tend to be effective and easy to apply.

For example, they help us understand the TOF spatial behavioral patterns; their presence; and their patterns of location, intensity, and volume. All this information is useful because it makes it possible to produce probabilistic models to spatiality mold surfaces of greater lengths. Having more areas where work is done with the LULC and TOF will allow us to examine the proportion, and it will create the possibility of producing new applied models for the domestic energy sector.

Technological advances in artificial intelligence and big data, with the development of innovative machine learning, deep learning algorithms and cutting-edge cloud computing, have achieved spectacular advances in automatic LULC generation. However, we are far from guaranteeing highly reliable results as it has been shown that data gaps or inconsistent and heterogeneous data continue to occur (Zhang and Li, 2022). The present research experience contributes to further advances in the generation of data with a high level of precision that can be used for the development of future models on this sector in India.

This study showed that high resolution images photointerpreted a map scale of 1:1,000 are the only way to achieve a reliable identification of TOF, from which we were able to calculate a rough estimate of the fuelwood supply that is not visible in other resolutions and scales. It is important to mention, the advantage of using Google earth is that it provides the latest satellite imagery having spatial resolution less than 1m. While the disadvantage is that it may not be possible to obtain the original multispectral band data and hence image classification using unsupervised or supervised techniques cannot be carried out. (Malarvizhi et al, 2016)

Another factor associated with resolution and scale is the minimum mapping unit (MMU), which makes it possible to conserve areas with small surfaces or those that are not very representative in cartographic terms. In our experience, we have proven that the size of the objects and patches of *Prossopis juliflora* fluctuate between 11 m^2 and 2600 m^2, elements that are imperceptible in terms of the MMU. In this case, determining the MMU is counterproductive because it contributes to underestimating the biomass, especially when there are high MMU values. Therefore, using small MMU values is recommended, with the aim of conserving most of the polygons, which are the base for quantifying the potential biomass for domestic use.

It is important to mention that the exploration of different approaches to identify and quantify TOF, on different geographical scales and with different sensors, is a trending research topic when it comes to using other tools such as LIDAR or UAV (Dai et al., 2018; Gomes et al., 2018; Aubry-Kientz et al., 2019) but up until now this exercise has proven to be complex, and there is still no agreement about best practices (Aubry-Kientz et al., 2019).

Regarding the reliability of the results, we had an overall reliability of 78.1 % for Landsat, 88.5 % for Sentinel, and 96 % for Google earth image. In general, the reliability of thematic maps has been accepted without questioning, but we must keep in mind that all of them have a degree of uncertainty, which mostly depends on the quality of the input and the methodology adopted for their development (Mas et al., 2003).

During the process of this study, we used GNSS Data Logger devices that were provided to the area locals who gather fuelwood. While these tools are quite useful and have been employed in various scientific studies, in terms of fuelwood, their applications have been rather basic. For example, they have been employed to identify the locations of trees used for fuelwood (Ramachandra, 2010) or to locate the areas impacted by their use (Shaheem et al., 2016).

In this study, applying the GNSS Data Logger devices reinforced the evidence about the uncertainty that is associated with medium and low resolutions when identifying scattered fuelwood sources. The cross validation showed that people apparently gathered fuelwood in agricultural areas, but fuelwood was actually harvested in scattered shrubland patches in the agriculture matrices that the sensors did not capture due to their size, as previously mentioned. Therefore, we consider that GNSS PS can be incorporated into fuelwood availability studies to better understand the collection patterns.

Finally, we compared the result of the three fuelwood estimates, considering the maximum and minimum values that were calculated based on the productivity data identified in the secondary sources. To do so, we used the cartography derived from each sensor as a base. The identified values were highly variable, even within the same country. This is because the quantity of biomass depends on factors such as the age of the trees and the environmental conditions they are found in, such as soil types, presence of humidity, etc. (Khanna, 2011; Pasiecznik et al., 2001). Moreover, productivity values are rare due to the scarcity of permanent sampling plots.

Although Trees Outside Forest (TOFs) have been little recognized in the evaluations of natural resources in large areas (Kleinn, 2000; Ashutosh, 2010), a great amount of research have been conducted on TOFs in terms of mapping and field-based fuelwood productivity estimates (Bellefontaine et al., 2002; Ramachandra, 2010; Doubrawa et al., 2013; Schnell et al., 2015).

In any case, and to our knowledge, no consistent comparison exists between accounting or not for TOFs in fuelwood supply-demand estimations; even though they can be the main source of woodfuel in many regions of the world. For example, in has been reported for southern India that up to 90% of the wood used in charcoal making comes from TOFs (Krishnankutty et al., 2008). No information could be found neither addressing sensor's resolution influence when mapping non-tree sources of fuelwood such as bushes or post-harvest crop residues (e.g. stalks, cobs, coconut shells, etc.).

We would like to emphasize that land cover and land use mapping are indispensable in several areas. So, this work also represents a contribution to the field of university teaching with satellite images (Martínez et al., 2015). For example, in the study programme of some Bachelor's and postgraduate degrees, they have courses of technology for geographic information with remote sensing and specific subjects for land covers and uses. That is the case of some undergraduate programs at ENES-Morelia, UNAM like: Geography, Geohistory, Geosciences, Environmental Sciences, Agroforestry Sciences, Ecology and Information Technologies in Science[5]. Our findings, regarding the certainty in the classification of land uses and the comparison of the different inputs and spatial scales will allow the generation of teaching practices through photointerpretation with a higher level of precision in the expected results, planning and implementation.

On the other hand, in the world of higher education, we are in the midst of developing and promoting online education, a trend that has been even more pronounced since the COVID-19 pandemic (Rapanta et al., 2020). Universities are increasingly interested in offering virtual campuses with online sessions and practical exercises (Plutino and Polito, 2017). In this context, this work provides new exercises that use practical cases of research and landscape analysis in remote regions, utilizing easily downloadable satellite images available online, without the need for high-end hardware. These are easily accessible tools (Sensu Palmentieri, 2022) for high-quality e-learning in geography, accessible to all social levels.

By using satellite images of different resolutions and data collected in the field from locals who gather firewood, we teach students to question and analyze spatial data, understand the limitations of these data, and apply spatial analysis methods in a more critical and reflective manner on real-world issues. This approach enhances their understanding and critical thinking skills (sensu Bearman et al., 2016) for teaching GIS.

5. Conclusion

The results indicated that spatial resolution and map scales play a significant role in fuelwood supply studies as uncertainty factors because they influence the availability of this resource, and thus they should be considered. Underestimates of fuelwood appear when not all the sources of domestic energy are considered, and such is the case of scattered or low-density vegetation. This happens because, often, they cannot be captured by sensors with medium or low resolution. However, when these elements are considered, the results might be the opposite, which could modify the current outlook of areas marked as deficient.

For studies analyzing the fuelwood supply in arid regions with predominating shrubland or agricultural land use, we recommend paying attention to the input data that is used to develop the cartographic bases. Given that areas of study with open and scattered vegetation have a need for input and methods that allow for capturing the different sources in detail, these data are fundamental for estimating the availability of fuelwood.

[5] https://www.enesmorelia.unam.mx/admision-licenciaturas/

Therefore, one of the challenges we face in the issue of wood for domestic use is tied to an accurate diagnosis of its availability. Accordingly, we believe incorporating elements such as spatial resolution and analysis geographical scale into studies on the availability of fuelwood can make it possible to discern new outlooks among scarcely vegetated regions with a predominance of agriculture and sparse shrubland and which have been marked as deficient in regional and global studies. This is true of some regions in south Asia – such as the case we are presenting here – and in east Africa, which are cataloged as hot spots where most of the demand for fuelwood is considered to be unsustainable (Bailis et al., 2015). Wood can be considered a conditionally renewable resource because trees grow naturally in many environmental conditions. If wood is harvested at or below the rate at which it naturally regenerates, then harvesting is sustainable. However, if more wood is harvested than the landscape can replace, as is often the case in low- and middle-income countries (where people rely heavily on fuelwood and charcoal), harvesting is not sustainable and tree cover will decline over time. This causes landscape degradation and may also contribute to long-term deforestation.

Despite advancements in geospatial technology, uncertainty about the availability of fuelwood in the different regions of the world remains. In particular, this is because the TOF are imperceptible in medium or low resolution. Consequently, the estimates of the availability of this resource are affected, thus underestimating or overestimating the biomass based on the spatial resolution and the interpretation method that was employed (Pandey, 2002; Shafeian et al., 2021).

Finally, we would like to highlight that this work addresses relevant issues in academic areas where the use of geotechnologies applied to territorial analysis and natural resource management are indispensable. We consider that in the field of teaching-learning, this study can encourage students' reflections about cartographic use and creation. As well, the application of remote sensing techniques and the influence of land cover and land use mapping in natural resource management. This paper wants to produce concerns in study topics associated with fuelwood collection patterns, fuelwood supply mapping, ecological impacts of biomass extraction, predictive models of fuelwood use, among others.

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