Mapping Bamboo Species in Agusan Del Norte, Caraga Region Using Remote Sensing and GIS Techniques

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Abstract: *Mapping naturally occurring bamboo is challenging due to the mingling with other land uses. This study used high-resolution PlanetScope satellite imagery with a 3-meter spatial resolution to map bamboo distribution using two classifiers: Support Vector Machine and Random Forest. The comparative analysis showed that SVM outperformed Random Forest, achieving higher accuracy rates in bamboo classification. Specifically, SVM achieved producer's and user's accuracy rates of 92.86% and 83.87%, respectively, demonstrating its precision in identifying bamboo species. The study estimated 1,840 hectares of bamboo and 4.44 million bamboo culms in the province, with 39.79% located in the Municipality of Buenavista. A bamboo database was created within GIS software linked to Microsoft SQL Server Management using field survey data and the classified map. Mapping the bamboo species in the province is crucial due to the ecological and economic significance of bamboo. Accurate mapping helps in understanding the distribution of bamboo species, identifying areas for conservation and sustainable harvesting. This research highlights the effectiveness of SVM in classifying bamboo species from satellite imagery and the potential of remote sensing and GIS technologies for efficient natural resource management in tropical regions like Agusan del Norte.*

Keywords: PlanetScope; Support Vector Machine; Random Forest; Bamboo database

1. INTRODUCTION

Bamboos are one of the known tropical grass-plant species that can grow everywhere in the tropical and subtropical countries such as the Philippines, and has high ecological value in the ecosystem [1]. It holds significance in providing goods and services essential for livelihoods because it can rejuvenate underground, requiring infrequent replanting, and minimal care and labor [2]. The growing awareness of the importance of the bamboo resources increases the demand for the inventory of the spatial bamboo information [3] through field survey and mapping using satellite images to improve the monitoring of the wide distribution of bamboo in the region and provide information on the quantity and types of bamboo present for the local community and for the government [4]. In countries where naturally grown bamboos are abundant, bamboo mapping is perceived to be challenging because these grasses are often dispersed, mixed with other vegetations and within forest understories [1].

Mapping the bamboo distribution using remote sensing method and spatial analysis such as Geographic Information System (GIS) requires sample data from field surveying especially in large scale region, the sample data that was collected can be used for visual interpretation for the land use and land cover classification (LULC) and inventory [4]. Using remote sensing technology in classification and mapping can be more cost-effective than traditional method [5]. The use of remote sensing can demonstrate the difference of spectral signatures of bamboos in other classes during the classification [6]. Machine learning has been used to reveal spatio-temporal patterns between the RS data and bamboo properties [3]. Classifiers such as Support Vector Machine (SVM) and Random Forest (RF) were used to map bamboo areas with up to 90% accuracy [3]. Training pixel points were identified and assigned for each pixel for a single LULC class [3]. RF is a strong algorithm that makes reliable predictions by combining the decisions of multiple decision trees. It is effective in preventing overfitting and is commonly used for land cover mapping and monitoring due to its ability to handle high-dimensional data efficiently [4]. SVM has been widely used in remote sensing and GIS for land cover classification, land use mapping, and other spatial analysis tasks [7]. In the study of Cruz, et. al, GIS tools were utilized to produce service area maps [8]. GIS was also used to map the suitability of Dragon fruit Farming in Butuan City, Agusan del Norte, Philippines [9].

Inventory assessment of bamboo involves categorizing, organizing, and evaluating bamboo resources based on characteristics like density, age, species composition, and health [10]. Several studies have used PlanetScope data for forest cover and structural mapping. It is crucial to consider spectral resolution and radiometric consistency. The frequent observation and high spatial resolution of PlanetScope data present new possibilities for land cover monitoring [11].

Agusan del Norte, situated in the northern part of Mindanao in the Philippines, is well-known for its plentiful and thriving bamboo forests [12]. To effectively utilize bamboo resources, a thorough and spatial analysis approach is essential, involving integrating advanced technologies such as remote sensing and GIS [13] to provide insights related to bamboo research and development in the Philippines. To support the need for mapping this resource, it is important to note the current status of bamboo utilization in Agusan del Norte province. Currently, not all bamboo varieties in the province are being fully exploited. Bamboo is in demand in the province for furniture use. Some companies have expressed interest in setting up operations in the province to meet this demand. This underscores the necessity for detailed mapping to better understand the distribution of bamboo species, which can aid in sustainable

management, conservation efforts, and maximizing the economic potential of this resource.
The main objective of this study is to conduct a province-wide mapping of bamboo species through remote sensing and field data observations. Specifically, this study aims to: (1) generate distribution maps of existing bamboo species in Agusan del Norte using remotely-sensed images and field data; (2) evaluate and compare the SVM and RF classifiers in mapping bamboo species; and (3) create a database of the identified bamboo species in Agusan del Norte. This study introduces the use of high-resolution PlanetScope satellite imagery with a 3-meter spatial resolution and compares two advanced machine learning classifiers (SVM and Random Forest) for bamboo mapping, showcasing the effectiveness and precision of these methods in a tropical region like Agusan del Norte.

2. STUDY AREA

The study area consists of the entire Agusan Del Norte (see Fig. 1), situated in Northeastern Mindanao at Caraga Region bordered by provinces of Surigao del Norte to the northeast, Surigao del Sur to the southeast, Agusan del Sur to the southwest, and Misamis Oriental to the northwest [13]. The approximate coordinates are Latitude: 9.1312° and Longitude: 125.5250° E. The province has a land area of 2,611.63 square kilometers or 1,008.36 square miles [14][15]. It has an average elevation of approximately 234 meters above sea level and has an irregular and mountainous geography [15]. Known for its diverse natural resources and landscapes and largely based on agriculture, with crops like rice, corn, coconut, and fruits being essential contributors. The municipalities present in the study are Kitcharao, Jabonga, Santiago, Tubay, City of Cabadbaran, Remedios T. Romualdez, Magallanes, Buenavista, Nasipit, Carmen, and Las Nieves.

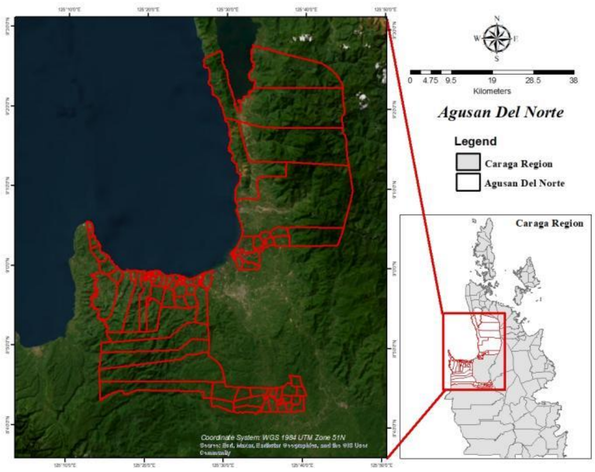

Fig. 1. Map of the study area.

3. MATERIALS AND METHODS

3.1 Data Collection

Planetscope satellite image data was downloaded in Planet Explorer Website (https://www.planet.com/explorer/) and was provided from one of the instructors at Caraga Center for Geo-Informatics (CCGeo), Caraga State University. The PlanetScope satellite images use optical sensor to capture imagery of the Earth's surface [16] that was acquired on April 13, 2023. Planetscope level 3B is a PlanetScope Ortho Tile Product, it is a radiometric and sensor corrections applied to the data. The imagery is orthorectified and projected to a UTM projection. The cloud cover percentage that was acquired of the Planetscope image was 2.98%. Planetscope data allows almost daily images over an area with a spatial resolution of 3 meters and eight (8) spectral bands, which is Band 1 (Coastal Blue), Band 2 (Blue), Band 3 (Green I), Band 4 (Green), Band 5 (Yellow), Band 6 (Red), Band 7 (Red Edge) and Lastly Band 8 (NIR).

3.2 Image Pre-processing of PlanetScope Image

The pre-processing of PlanetScope image involve several steps to improve the data quality of the image. The following pre-processing that was applied: Radiometric correction, Geo-Correction, Elevation Correction and Atmospheric correction. Radiometric Correction of the PlanetScope remove sensor-specific variations and atmospheric effects from the raw digital numbers (DN) recorded by the satellite sensors, converting them into calibrated reflectance values. Geo-correction, also known as geometric correction or orthorectification, is a crucial pre-processing step for PlanetScope satellite imagery to accurately align the imagery with a map projection or coordinate system and remove geometric distortions caused by sensor orientation, Earth curvature, and terrain variations. Geo-correction ensures that each pixel in the image corresponds to a precise location on the Earth's surface, enabling accurate spatial analysis and integration with other geospatial datasets [16]. Elevation correction, also known as terrain correction, is a pre-processing step used to account for terrain-induced distortions in satellite imagery, particularly in areas with significant topographic relief. This correction is important for accurate analysis and interpretation of the imagery, as terrain variations can affect the geometric and radiometric properties of the image pixels [16]. Atmospheric correction is a critical pre-processing step for PlanetScope satellite imagery to remove the effects of atmospheric scattering and absorption, resulting in more accurate and consistent reflectance values across the image. Atmospheric correction enhances the usability of the imagery for various applications such as land cover classification, vegetation monitoring, and change detection by minimizing atmospheric distortions and improving the comparability of pixel values [16]. The pre-processed PlanetScope image will have a Geodetic projection of WGS 84/UTM Zone 51N and spatial resolution of 3 meters with optical sensor.

3.3 Ground Validation Surveys

The field data collection process for the bamboo inventory involved collaboration between the community under the Department of Labor and Employment (DOLE) and the researchers. Various physical parameters were acquired during the survey to comprehensively characterize bamboo stands in the study area. The physical parameters are the following: local name of the bamboos, type of species, location, number of clamps and Geo-tagging points. Geo-tagging of points was collected on-site for validation to supplement satellite data. This process is necessary to ensure the exact points or coordinates of the existing bamboos across the province including all the varieties of the existing bamboos and will be used for accuracy assessment. The common or indigenous names used by the local community to refer to different bamboo species. This information helps identify and categorize bamboo varieties based on local knowledge. Species present in the study area to distinguishing between different bamboo species. The quantity of bamboo culms or individual bamboo plants observed at each surveyed location. This parameter provides information on the density and distribution of bamboo stands across the landscape. The bamboo plots were collected in various municipalities across the province of Buenavista with 70 plots, Carmen with 85 plots, Jabonga with 71 plots, Kitcharao with 40 plots, Nasipit with 71 plots, and Santiago with 72 plots. Furthermore, the collected information will be used for training and validation processes.

Fig. 2. Photos acquired during the field measurements.

Table 1. Bamboo species

Species	Scientific Name	Number of plots
Botong	Dendrocalamus Latiflorus	153
Lunas	Bambusa Nguyenii	83
Kiling	Bambusa Vulgaris	36
Bayog	Bambusa Merrilliana	34
Tunokon	Bambusa Blumeana	77
Bolo	Gigantochloa Levis	5

3.4 Generation of Bamboo Distribution Maps

To generate a bamboo distribution map using PlanetScope satellite imagery, the researchers used two classifiers namely, Support Vector Machine and Random Forest, in the classification of bamboo. Support Vector Machine (SVM) is a supervised machine learning technique that may be used to problems involving regression or classification [17]. The primary purpose of SVM is to find a hyperplane that best separates data points into different classes or predicts a continuous target variable [18]. This algorithm use the features extracted from the images to differentiate between different bamboo species. Random Forest is a powerful ensemble learning algorithm used for both classification and regression tasks, establishing of decision trees during training and outputs the mode of the classes [19]. In the

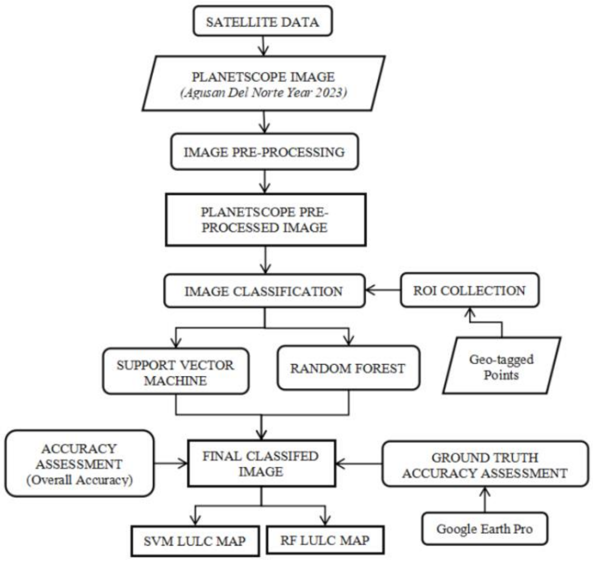

Fig. 3. Bamboo Mapping Process

process of classifying the PlanetScope image using GIS software, Support Vector Machine (SVM), and Random Forest algorithms, the researchers started by selecting a set of training samples. These samples serve as representative examples of different land cover types, including bamboo, that are used to train the classification algorithms. For SVM and Random Forest classification, the researchers utilized this set of training samples to teach the algorithms how to distinguish between different land cover classes based on their spectral characteristics. The training samples provide the algorithms with labeled examples of bamboo and other land cover types such as Built-Up, Cropland, Barren, Water, and Forest allowing them to learn the patterns and relationships in the satellite imagery data.

Once the classification was completed, the researchers conducted an accuracy assessment to evaluate the performance of the classification algorithms. This assessment involved comparing the classified image with ground truth data, such as google earth pro and imported geo-tagged photos onto the raw image to serve as reference training samples specifically for bamboo. These photos, captured on the ground and linked to their corresponding locations in the satellite image, provide valuable reference points for identifying and characterizing bamboo vegetation. Common accuracy metrics used include overall accuracy, which measures the proportion of correctly classified pixels in the image, and kappa coefficient, which assesses the agreement between the classified and reference data while accounting for chance agreement. Finally, the researchers generated a final classified map depicting land cover and land change using the SVM and Random Forest classification results. This map provides valuable insights into the spatial distribution of bamboo and other land cover classes in the study area, highlighting areas of vegetation change, habitat fragmentation, or land use transitions over time.

The accuracy assessment of classifying PlanetScope images with Support Vector Machine (SVM) and Random Forest (RF) classifications involves comparing the classified results with reference data or ground truth information. First, collect ground truth data through field surveys or existing datasets that accurately represent the land cover classes in your study area. Next in GIS software, create validation points or polygons based on the reference data. These points or polygons should be randomly distributed across the study area and represent different land cover classes. Use the SVM and RF classification algorithms to classify the validation points or polygons based on the input satellite imagery. Compare the classified land cover classes with the reference data to assess classification accuracy. Lastly, the Spatial Analyst extension or other relevant tools to calculate accuracy metrics such as overall accuracy, producer's accuracy, user's accuracy, kappa coefficient, and other relevant statistics. These metrics provide quantitative measures of classification accuracy.

3.5 Bamboo Area and Density Calculation

The total bamboo area was obtained by utilizing the bamboo distribution map, which exhibited relatively higher accuracy. It was calculated as the aggregate of all bamboo cover pixels multiplied by the pixel dimension.

The formula provided below serves to compute bamboo density. This equation offers an indication of the density or concentration of bamboo clusters within a designated land area. This metric proves valuable for comprehending the spatial distribution and abundance of bamboo stands, crucial for proficient management and conservation of bamboo resources.

$$\text{Density}_{\text{Bamboo}} = \frac{Number\ of\ Bamboo\ Culms\ (Poles)}{Bamboo\ Land\ Area}$$

Equation 1. Equation of Bamboo Density

The bamboo density and the total bamboo area were used to estimate the total number of bamboo culms (poles) for the whole province.

3.6 Database Creation

The researchers created a database that serves as a fundamental resource for understanding the distribution and diversity of bamboo species within the study area. This database typically contains comprehensive information about various aspects of bamboo, including the municipalities, barangays, area of bamboo and the estimated number of bamboo culms. By consolidating and disseminating valuable information on bamboo species, such databases empower local communities and stakeholders to make informed decisions and take proactive measures to ensure the long-term sustainability and resilience of bamboo ecosystems.

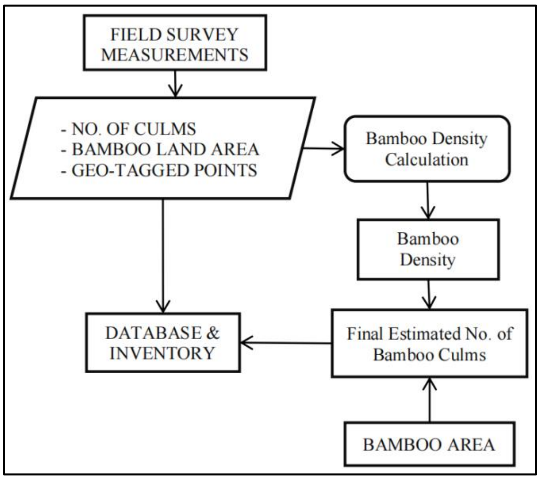

Fig. 4. Database and Inventory Process

Bamboo inventory assessment, the researchers conducted field survey measurements to gather detailed information about bamboo stands in the study area. These field surveys involved collecting various data parameters related to bamboo culms, including geo-tagged points and species identification. The researchers systematically visited locations within the study area where bamboo stands were present. At each location, precise geographic coordinates (latitude and longitude) were recorded using GPS devices or other geospatial tools. These geo-tagged points served as reference locations for the bamboo inventory assessment and were used to link field observations with corresponding locations in the satellite imagery. By collecting these field survey measurements and data parameters, the researchers obtained comprehensive information about bamboo stands in the study area. This detailed inventory data served as a valuable resource for analyzing bamboo distribution, abundance, growth dynamics, and ecological characteristics, supporting informed decision-making and management strategies for bamboo resources and ecosystem conservation.

4. RESULTS AND DISCUSSIONS

4.1 Distribution Maps of Bamboos

The distribution maps of bamboo within the study area were generated using RF and SVM classifiers trained on PlanetScope satellite imagery data and ground truth samples. Fig. 5 and 6 show the LULC map that provides valuable insights into the spatial distribution of bamboo across the landscape. The classification process yielded a detailed representation of areas where bamboo is present, allowing for the identification of bamboo-rich zones and potential bamboo habitats. The map exhibits varying degrees of bamboo coverage, with some areas showing dense bamboo clusters while others indicate sparse bamboo populations.

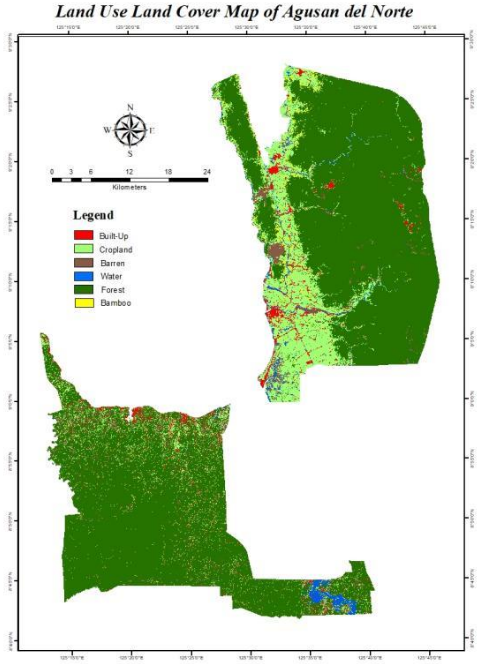

Fig. 5. LULC Map of Agusan del Norte Year 2024 using Random Forest

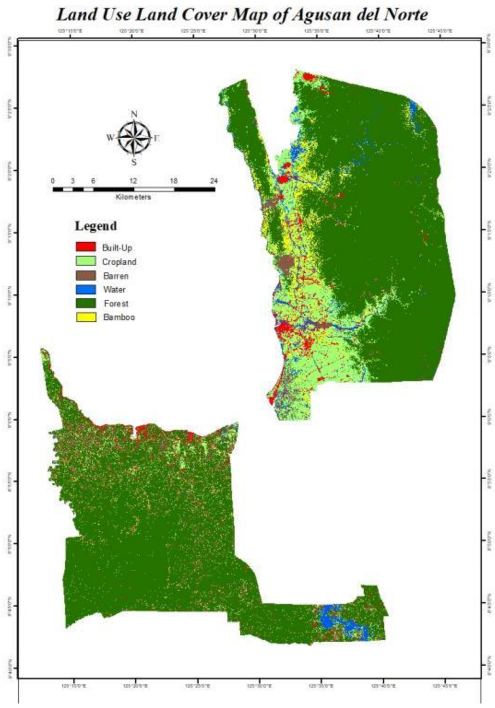

Fig. 6. LULC Map of Agusan del Norte Year 2024 using Support Vector Machine

Fig. 7 and 8 provide a clear visualization of the bamboo distribution across Agusan del Norte, with the use of gray to represent other land cover classes and yellow to highlight bamboo areas. The contrasting results from the Random Forest and SVM classifiers offer valuable insights into the spatial patterns of bamboo presence within the region. The scattered distribution observed in the Random Forest classification suggests a more dispersed arrangement of bamboo patches, potentially indicating diverse environmental conditions or human land use activities. Conversely, the concentrated clusters identified by the SVM classifier imply areas of dense bamboo growth, which could signify favorable ecological conditions or specific habitat preferences for certain bamboo species.

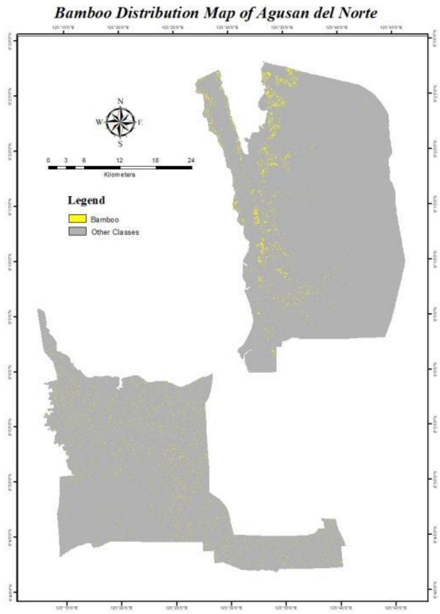

Fig. 7. Bamboo Distribution Map Year 2024 using Random Forest

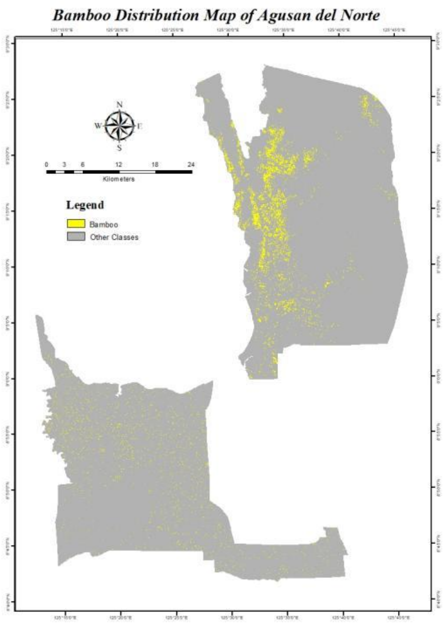

Fig. 8. Bamboo Distribution Map Year 2024 using Support Vector Machine

The researchers opted for the false color band combination (Fig. 9) to facilitate the identification of bamboo extents in the PlanetScope image. This combination typically involves assigning near-infrared (NIR) to the red channel, red edge to the green channel, and red to the blue channel. This arrangement enhances the contrast between vegetation and other land cover types, making it easier to distinguish bamboo from surrounding features. The near-infrared band is particularly useful for highlighting healthy vegetation, as it reflects strongly in this spectral range.

Fig. 9. Band combination of NIR (Band 8), Red Edge (Band 7), Red (band 6)

The accuracy (see Tables 2 & 3) of the distribution map was assessed through validation against independent ground truth data, revealing a high level of agreement between the classified results and actual bamboo presence on the ground. This validation process strengthens the reliability and credibility of the distribution map, affirming its utility for informing bamboo conservation and management efforts.

Table 2. Confusion matrix and overall accuracy of bamboo using Support Vector Machine

Class Name	Built-up	Cropland	Barren	Water	Forest	Bamboo	Total	User's Accuracy
Built-up	56	1	2	1	0	0	60	93.33%
Cropland	0	53	3	1	0	0	57	92.98%
Barren	1	0	49	0	12	0	62	79.03%
Water	0	1	0	49	0	1	51	96.08%
Forest	0	0	1	0	53	3	57	92.98%
Bamboo	0	0	2	2	2	56	62	83.87%
Total	57	55	57	53	67	60	349	
Producer's Accuracy	98.25%	94.64%	84.48%	92.45%	76.81%	92.86%		Overall Accuracy = 89.40%

Table 3. Confusion matrix and overall accuracy of bamboo using Random Forest

Class Name	Built-up	Cropland	Barren	Water	Forest	Bamboo	Total	User's Accuracy
Built-up	56	3	1	0	0	0	60	93.33%
Cropland	2	49	0	0	1	0	52	94.23%
Barren	0	0	49	0	7	0	56	87.50%
Water	0	2	0	45	2	1	50	90.00%
Forest	0	3	1	0	47	4	55	85.45%
Bamboo	0	0	1	2	7	50	60	73.33%
Total	60	54	50	50	63	56	333	
Producer's Accuracy	96.55%	85.96%	92.45%	95.74%	68.12%	89.80%		Overall Accuracy = 87.09%

4.2 Ccomparative Aassessment of SVM and RF

The comparative analysis of the SVM and RF classifiers' confusion matrices shown in Tables 2 and 3 reveals that the SVM outperforms RF in terms of producer's and user's accuracy of bamboo, with a variation of accuracy rate of 92.86% and 83.87% respectively, compared to RF which has an accuracy of 89.80% and 73.33% respectively. Moreover, when considering the overall accuracy and kappa coefficient, SVM demonstrates superior performance, achieving a value of 89.40% and 87.28% respectively, compared to RF's lower values of 87.09% and 84.50% respectively. These results show that SVM is more effective than RF in accurately classifying bamboo species from satellite imagery particularly in PlanetScope image. The higher overall accuracy and kappa coefficient indicate that SVM provides more reliable and consistent classification results, making it a preferred choice for bamboo classification tasks. The interpretation accuracy for identifying land use and land cover categories from remote sensor data should meet a minimum threshold of 85 percent [20].

Fig. 5 and 6 present the results of the researchers' classification efforts, where regions of interest (ROIs) were delineated using polygons for training and points for accuracy assessment. Various land cover classes such as built-up areas, croplands, barren lands, water bodies, forests, and bamboo were identified and separated within the study area. Remarkably, in the classification of bamboo, the researchers computed omission and commission errors for SVM at 7.44% and 16.13% respectively. In contrast, omission and commission errors for RF were recorded at 10.20% and 26.67% respectively, suggesting that SVM yields more dependable and consistent classification outcomes compared to RF. This observation is mirrored in the producer's accuracy and user's accuracy, underscoring the classification's high caliber and dependability. The producer's accuracy measures how well the classes are classified, with errors reflected in the omission error. On the other hand, the user's accuracy gauges the reliability of the maps, encompassing both commission error and accuracy. This information is valuable for decision-makers involved in land cover mapping, biodiversity assessment, and natural resource management, as it highlights the importance of selecting appropriate classification algorithms for achieving accurate and reliable results.

4.3 Bamboo Area and Density Calculation

The number of culms can vary depending on the bamboo species and the specific characteristics of the land area. To estimate the land area covered by bamboo, satellite images are often utilized to digitize bamboo pixels, providing a visual representation of bamboo coverage across the landscape. By analyzing these digitized bamboo pixels, researchers can derive an approximation of the land area occupied by bamboo within the study area.

The relationship between the number of bamboo culms and the resulting land area (hectares) is evident from the data obtained through digitized satellite imagery. There is a direct correlation between the number of bamboo culms and the calculated land area covered by bamboo. Specifically, as the number of bamboo culms increases, the corresponding land area occupied by bamboo also tends to increase. The smallest number of bamboo culms recorded is 21 culms, covering an approximate land area of 0.01 hectares. The median record comprises 50 bamboo culms, encompassing an approximate land area of 0.02 hectares. The largest number of bamboo culms recorded amounts to 98 culms, occupying an approximate land area of 0.04 hectares. The data has been collected and validated in the field. With the provided sample of the number of bamboo culms and land area, the researchers calculated the bamboo density to be 2,414 culms per hectare. Multiplying the bamboo density result and the bamboo area calculated from the bamboo distribution map, the researchers achieved the estimated number of bamboo culms.

Using the bamboo density and the bamboo area from the bamboo distribution map, the researchers estimated a total number of 4.44 million culms in the province, where 39.79% comes from the Municipality of Buenavista. This information vary in bamboo distribution and density across different species within the study area. Species such as Lunas, Tunokon, and Botong are characterized by higher and lower clump numbers and occupy larger land areas, indicating their prevalence and abundance in the region, suggesting their comparatively limited presence or distribution. While the Bamboo Species of Kiling, Bayug, and Bolo are characterized in a moderate level of distribution and density compared to other bamboo species. Understanding the distribution patterns of these species is important to the biodiversity conservation efforts, land use planning, and ecosystem management strategies aimed at maintaining healthy and resilient bamboo ecosystems in the region.

4.4 Database and Inventory Assessment of bamboos

Fig. 9 presents the database and inventory assessment of identified bamboo in Agusan del Norte per municipality, except to the city of Butuan. This data was collected through a collaborative effort between the community under the Department of Labor and Employment (DOLE) and the researchers. The physical parameters obtained during the field survey include: Local name of the bamboo species, scientific name, date collected, estimated date planted, estimated date of harvest, number of bamboo culms and lastly the coordinates of the bamboo's. The dataset serves as a valuable resource for understanding bamboo distribution, habitat characteristics, and ecosystem dynamics in Agusan del Norte, contributing to informed decision-making and sustainable management practices.

Inventory assessment provides essential data on the distribution, abundance, and health of bamboo resources. The common species discovered in the area include Lunas, Tunokon, Botong, Bayug, Kiling, and Bolo. It can be seen in the inventory that the number of culms observed varies, with most bamboo specimens having a count ranging from less than 21 to more than 98. By conducting inventories, we can identify areas of high biodiversity value, prioritize conservation efforts, and implement measures to protect endangered species and habitats.

Utilizing field survey data and the classified map, the researchers established a bamboo database within GIS software connected to Microsoft SQL Server Management as shown in Figure 11. This software offers a user-friendly interface enabling users to engage with SQL Server databases, run queries, design and adjust database components, and undertake diverse administrative functions. By leveraging the powerful spatial analysis capabilities of GIS and the advanced database management features of SQL Server, this system supports data-driven decision-making, enhances the accuracy of inventory assessments, and aids in the development of targeted conservation and sustainable management strategies for bamboo resources. This interconnected system ensures data integrity, improves data accessibility, and enables complex spatial queries and analyses, ultimately contributing to more effective and informed bamboo resource management.

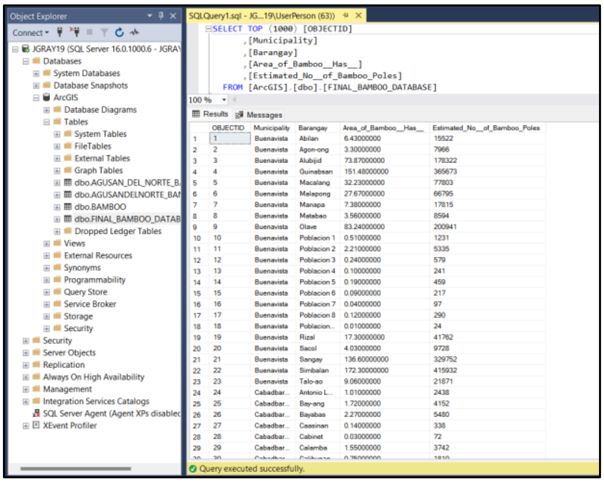

Fig. 10. Bamboo database integrated into GIS software and linked to Microsoft SQL Server Management.

5. CONCLUSIONS

The integration of PlanetScope high-resolution satellite imagery and ground truth data helps to delineate bamboo distribution areas and identify different bamboo species within the study area. The results of the study reveal significant insights into the spatial distribution and abundance of bamboo species in Agusan del Norte. The researchers identified several key areas with high bamboo density, indicating potential hotspots for bamboo conservation and sustainable management efforts. When comparing both classifiers, SVM proves to be more effective than RF in precisely classifying bamboo species from satellite imagery, especially in PlanetScope images. Furthermore, the classification results provide valuable information on the distribution patterns of different bamboo species, aiding in the characterization of the local bamboo ecosystem. The bamboo distribution map and density estimates can be utilized by environmental entities in the province.

Overall, this study contributes to the existing knowledge based on bamboo resources in Agusan del Norte and highlights the importance of remote sensing and GIS technologies in natural resource management and conservation. By providing accurate and up-to-date information on bamboo distribution, the findings can inform decision-making processes and support initiatives aimed at promoting the sustainable utilization of bamboo resources in the region.

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