

Sago mapping in Papua for remote-sensing-based resource characterization: A review

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ABSTRACT

Sago palm (*Metroxylon sagu* Rottb.) is an important ecological, economic, and cultural resource in Papua, Indonesia. This review examines the development of sago research and mapping technologies relevant to its spatial characterization in Papua. The literature was synthesized thematically to identify major research patterns, methodological developments, and remaining knowledge gaps. Previous studies have generated substantial knowledge on sago habitat, biological characteristics, productivity, genetic diversity, and utilization; however, these findings remain spatially and thematically fragmented and are only weakly connected to spatial mapping. Meanwhile, mapping technologies have progressed from habitat- and vegetation-level assessment toward object-, stand-, and individual-plant-level approaches through high-resolution imagery, UAVs, hyperspectral data, LiDAR, and advanced classification methods. To address this disconnect, this review proposes a four-stage multiscale framework linking (1) regional habitat screening, (2) stand and crown mapping, (3) biological classification, and (4) productive-attribute calibration. The framework provides a basis for shifting sago mapping beyond spatial presence toward biologically meaningful information on stand characteristics and resource potential, supporting more effective inventory, management, and sustainable utilization of sago resources in Papua.

Keywords: *Metroxylon sagu*, Papua, remote sensing, sago mapping, stand mapping.

INTRODUCTION

Sago palm (*Metroxylon sagu* Rottb.) is an important food resource in eastern Indonesia and is closely linked to the lives of the people of Papua. In addition to being a staple food source (Dimara and Auri, 2023; Putri et al., 2020), sago plays a role in meeting household needs (Fitriyah et al., 2025) and holds social and cultural value in the lives of Indigenous Papuans (Kadir et al., 2022; Sidiq et al., 2022). Its ecological characteristics, which allow it to grow in wetlands (Okazaki and

Sasaki, 2018), swamps (Karim, 2021), areas near water sources (Sarie et al., 2023), and lowlands (Dimara et al., 2021), make sago an important component of ecosystems and local food systems (Sarie et al., 2023).

Geographically, sago resources in Indonesia are not only found in Papua but are also distributed in Maluku (Botanri et al., 2022), North Maluku (Hasan et al., 2024), Riau (Liska Ayulia et al., 2021), Sulawesi (Yusuf et al., 2023), and Kalimantan (Abbas et al., 2009). The diversity of habitat conditions and utilization patterns

among regions makes information regarding the extent, distribution, and spatial characteristics of sago important for supporting the management of these resources. Several studies outside Papua have used spatial approaches to describe the distribution and ecological characteristics of sago. For instance, on Seram Island, Maluku, the supervised classification of Landsat-5 TM imagery combined with field verification has been used to identify the spatial distribution and potential of sago, as well as its association with lowland, coastal, riverine, and alluvial environments (Botanri et al., 2022).

The availability of information regarding the presence and condition of sago is becoming increasingly important to support the inventory, management, and utilization of resources over large areas. Field surveys can provide detailed information about plant conditions, but their implementation over extensive regions requires significant time and resources (Letsoin et al., 2022). Remote sensing offers a more efficient approach to repeatedly obtain spatial information, with sensor and image resolution developments enabling vegetation monitoring at increasingly detailed levels (Putra and Wijayanto, 2023). These advancements have been accompanied by a shift in analytical approaches, from pixel-based classification to object-based analysis, as well as the use of machine learning and deep learning algorithms to distinguish vegetation types and identify plant objects (Akhtar et al., 2023).

At the individual level, mapping is no longer aimed solely at determining the presence of vegetation but also at detecting the position, canopy boundaries, and characteristics of each plant (Mao et al., 2025). This shift in scale increases the demand for high-resolution imagery, representative reference data, and validation methods capable of evaluating object-level results (Casapia et al., 2025). The tree mapping literature shows that result accuracy is determined not only by the algorithm but also by data quality, environmental conditions, mapping units, sampling strategies, and the suitability of reference data to the identified objects. In the context of sago, these developments are important because information regarding sago habitat and cover has not fully addressed the need for plant identification at the stand or individual levels. Therefore, a synthesis is needed that links the development of sago research with changes in data, objects, classification methods and mapping validation.

Although research on sago in Papua has expanded across ecological, biological, genetic, and utilization aspects, the available knowledge remains fragmented across various research themes and geographic areas. In parallel, developments in remote sensing and geospatial technologies have provided increasingly detailed approaches for mapping vegetation and individual plants. However, the connection between knowledge of sago characteristics and the development of appropriate spatial mapping approaches remains insufficiently discussed in the literature. A broader synthesis is therefore needed to understand how the biological and ecological characteristics of sago can inform mapping approaches, from regional habitat screening through stand and crown mapping, biological classification, and productive-attribute calibration.

This study aimed to review the development of sago research and mapping technology in Papua, with particular attention to the progression from ecological and biological characterization to spatial mapping. It also discusses opportunities to integrate remote sensing, geospatial analysis, and advanced image classification techniques across regional habitat screening, stand and crown mapping, biological classification, and productive attribute calibration.

DISTRIBUTION OF SAGU IN PAPUA

Research on sago in Papua has been conducted across landscapes with diverse environmental characteristics, ranging from watersheds, lakes, and wetlands to archipelagic regions and areas experiencing land cover changes (Azhar et al., 2020; Dimara et al., 2023; Dimara and Auri, 2023; Letsoin et al., 2020; Nurulhaq et al., 2022; Rembon et al., 2008; Yamamoto et al., 2020a, 2020b). The Sentani watershed and the area around Lake Sentani are among the most studied regions because of the presence of sago habitats in dryland, temporarily inundated, and long-term inundated conditions, as well as the diversity of local varieties (Azhar et al., 2020; Dimara et al., 2023; Rembon et al., 2008; Yamamoto et al., 2020a; Yamamoto et al., 2020b). In the Yapen Islands, research has been conducted on landscapes influenced by landforms, altitude, slope gradient, soil characteristics, rainfall, and distance from the coast (Dimara and Auri, 2023). Different conditions were found in Merauke, which was studied in the context of land cover change and the potential loss of natural sago habitat (Letsoin et al.,

2020), while the Haripau area in Mimika has been used to study the accession diversity and characteristics of sago plants (Nurulhaq et al., 2022). This diversity of landscape conditions indicates that sago research in Papua is not limited to a single type of environment but encompasses ecosystems with different hydrological, topographical, and land cover characteristics.

The differences in regional characteristics are reflected in the research objectives. In the Sentani region, research has been directed toward understanding growth, productivity, biomass, regeneration, and plant responses to environmental conditions, including drought and flooding (Rembon et al., 2008; Yamamoto et al., 2020a, 2020b; Azhar et al., 2020). Research in the Sentani watershed and Yapen Islands broadened the objectives to include the identification of production potential, suitability, and habitat distribution based on environmental characteristics (Dimara et al., 2023; Dimara and Auri, 2023). In Mimika, the research objectives focus more on morphological characterization and differences in production potential among accessions (Nurulhaq et al., 2022), while research in the Yapen Islands also includes an evaluation of starch quality and its utilization potential (Moeljono et al., 2025). At the molecular level, research has been directed toward revealing the genetic diversity and intraspecific characteristics of *M. sago* using genetic markers (Abbas et al., 2020, 2021). Research in Merauke has taken a landscape change perspective to evaluate

the implications of land cover change for the existence of natural sago habitats (Letsoin et al., 2020). Thus, the research objectives demonstrate the scope of the study, covering growing environments, plants, productivity, genetic resources, product quality, and landscape change.

Studies focusing on individual sago plants generally employ field observations and measurements of growth characteristics, stem size, biomass, leaves, starch production, and morphological characteristics of the plants. Some of these previous studies also incorporated interviews with local communities and sago farmers as part of their field-based investigations (Rembon et al., 2008; Yamamoto et al., 2020a, 2020b; Nurulhaq et al., 2022). Physiological studies have used experimental approaches to evaluate the response of sago to drought and inundation by measuring parameters such as gas exchange, net assimilation rate, and chlorophyll fluorescence (Azhar et al., 2020, 2021). To examine genetic diversity, molecular approaches have been applied using DNA extraction, amplification, and analysis of chloroplast gene sequences, including *matK* and *nad2* (Abbas et al., 2020, 2021). Habitat studies have begun to combine field surveys with spatial analysis and multispectral imagery, including Landsat 8 and QuickBird, to identify sago habitat distribution and suitability (Dimara et al., 2023; Dimara and Auri, 2023). Remote sensing approaches have also been used to analyze land cover changes over the period 1990–2019 in Merauke (Letsoin et al., 2020). The

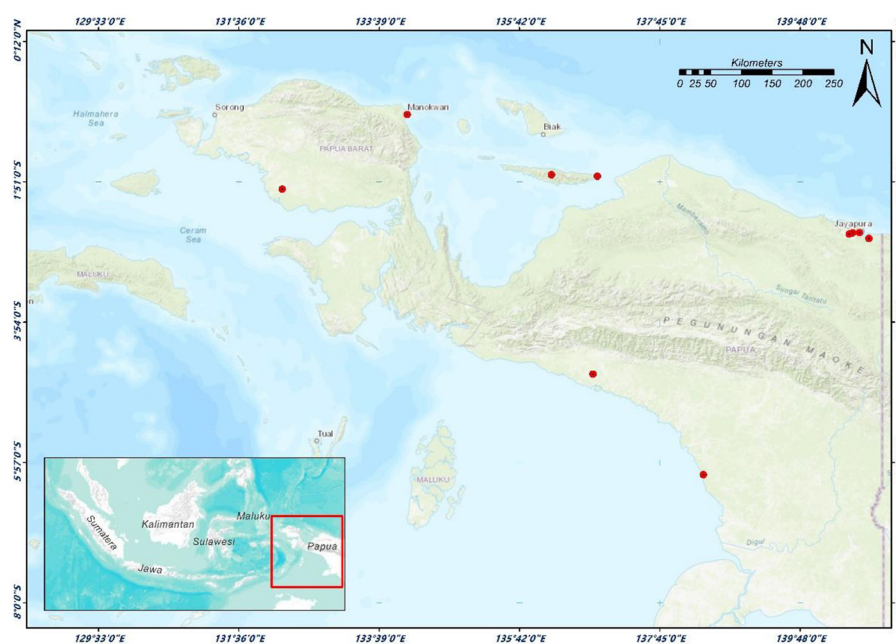


Figure 1. Spatial distribution of sago palm locations in Papua, Indonesia

diversity of these approaches demonstrates that sago research in Papua is evolving from direct observation of the plant and its environment toward the use of spatial data and molecular analysis, enabling characterization of sago resources at both broader and more specific scales (Figure 1).

AREAS OF SAGO STUDIES

Research on sago in Papua has expanded from studies on distribution, habitat, growth, biomass, regeneration, and environmental characteristics to increasingly diverse research areas, including starch productivity, morphological characteristics, physiological responses, genetic diversity, starch quality, utilization, and spatial analysis (Pasolon, 2015; Rembon et al., 2008; Yamamoto et al., 2020a, 2020b; Abbas et al., 2020, 2021; Azhar et al., 2020, 2021; Letsoin et al., 2020; Dimara et al., 2023; Dimara and Auri, 2023; Moeljono et al., 2025). This development reflects an increasing effort to understand sago not only as a plant and ecological resource but also in terms of its biological characteristics, productivity, genetic resources, utilization potential, and spatial distribution. Based on these developments, the review synthesized into six main areas: (a) distribution and habitat, (b) stand structure and productivity, (c) genetic diversity, (d) morphological characteristics, (e) starch quality and utilization, and (f) remote sensing and spatial mapping.

Distribution and habitat

Changes in land cover and biophysical characteristics have become important aspects of understanding the distribution and presence of *Metroxylon sago* habitats. An analysis of land cover change in Merauke from 1990 to 2019 showed that 12 out of 20 districts experienced a tendency toward loss of natural habitat suitable for sago, indicating pressure on the existence of sago habitat (Letsoin et al., 2020). Environmental conditions are also related to the variation of sago types between regions, as shown by differences in soil, groundwater table, rainfall, and temperature, with more than seven types found in Sentani, five types in Maba, and three types in Southeast Sulawesi (Pasolon, 2015). On a spatial scale, sago habitats in the Sentani Watershed can be distinguished as drylands, seasonally

inundated land, and permanently inundated land, and include 13 local varieties based on the Sentani language (Dimara et al., 2023). In the Yapen Islands, the distribution of sago habitats is related to landforms, slope gradient, elevation, soil characteristics, rainfall, and distance from the coast (Dimara and Auri, 2023). Hydrological conditions also affect the physiological responses of sago; drought can reduce leaf gas exchange, photosynthetic activity, and chlorophyll fluorescence, whereas prolonged inundation can reduce photosynthetic capacity despite the ability of sago to tolerate flooding over certain periods (Azhar et al., 2020, 2021). These findings indicate that the focus of studies has shifted from identifying changes and the existence of habitats to a more specific understanding of biophysical characteristics and the response of sago to its environmental conditions.

Stand structure and productivity

Research on stand structure and sago productivity has shown that age, stem characteristics, and biomass are related to starch production. Stem length, diameter, weight, and volume change with growth and are linked to starch productivity, whereas leaf scars, leaf number, and pith characteristics can be used as indicators of development and harvest stage (Yamamoto et al., 2020a; Yamamoto et al., 2020b). Productivity also varies among varieties and accessions; differences in starch production have been found among cultivars in the Yapen Islands, while the Tuhai accession produced the highest starch yield in Haripau, although it had a higher ash content and, therefore, lower starch quality (Moeljono et al., 2025; Nurulhaq et al., 2022). Differences in productivity are also related to growth characteristics, with early flowering varieties having a shorter growth period but smaller stem sizes than late-flowering varieties (Yamamoto et al., 2020a). In addition to plant characteristics, environmental conditions also affect physiological processes; drought decreases photosynthetic activity, although its direct impact on starch or biomass production has not yet been measured (Azhar et al., 2021). Overall, research remains dominated by field measurements; therefore, the relationship between stand structure and productivity indicators with characteristics that can be extracted from remote sensing data is still limited.

Morphological characteristics

The morphological characteristics of sago exhibit clear variation between varieties and throughout plant growth. These differences encompass spine, stem, leaf, and pith traits, with the Mapartaro accession having the largest leaf area (23.56 m²) compared to other dominant accessions in Haripau (Nurulhaq et al., 2022). Around Lake Sentani, variations in stem length and diameter also distinguish the growth characteristics of different varieties (Yamamoto et al., 2020a). Meanwhile, leaf and stem characteristics display a consistent pattern of change according to plant age, particularly in the number and size of leaves, as well as stem length, diameter, and weight (Yamamoto et al., 2020b). Morphological variation is also found in spine characteristics between regions and in the size of fruit and seeds in wild sago Manno Kecil and Manno Besar (Pasolon, 2015; Rembon et al., 2008). These findings indicate that sago morphology reflects two main sources of variation: inter-varietal differences and ontogenetic changes during growth, so that morphological characters can serve as an important basis for distinguishing and identifying sago types.

Genetic diversity

Research on sago genetic diversity has begun to utilize molecular markers, particularly the *matK* and *nad2* genes, to identify genetic variation and phylogenetic relationships among accessions. The *matK* gene is a chloroplast DNA marker widely used in DNA barcoding for species identification and authentication, whereas *nad2* is used as an additional marker to observe genetic variation at the intraspecific level. Analysis of 15 Papua sago accessions using *matK* revealed two genotypes, while *nad2* showed only one haplotype and *matK* showed two haplotypes, with relatively low genetic variation observed in both markers (Abbas et al., 2020; Abbas et al., 2021). Several accessions of the second genotype have been proposed as new varieties based on their molecular characteristics (Abbas et al., 2021). In addition, *matK* has proven to be effective as a DNA barcode for distinguishing *M. sagu* from other palms and supporting germplasm authentication (Abbas et al., 2020). Overall, research in this area indicates that studies of sago genetic diversity are still focused on molecular

characterization, genotype identification, and germplasm authentication, with the scope of genetic variation remaining limited to the markers and accessions analyzed.

Starch quality and utilization

Sago starch production differs among varieties, changes in line with plant development, and is related to stem and pith characteristics. The Para variety yields an average starch content of 67.6 kg/tree, with a maximum of 975 kg/tree, which is closely associated with the dry weight of the pith, as well as stem volume and weight (Yamamoto et al., 2020b). Starch content increases up to a certain stage before flowering, indicating a change in starch accumulation during plant development (Yamamoto et al., 2020a). Inter-varietal differences are also observed in yield and starch characteristics in the Yapen Islands; Noyn yields the highest at 630 kg/tree, while Kurai, Huworu, and Woru have potential for food use, whereas Maku-bong and Dami are more suitable for non-food applications (Moeljono et al., 2025). These findings demonstrate that research focus has shifted from quantity measurement of starch to quality characterization and classification of utilization potential based on variety.

Remote sensing and spatial mapping

Mapping research on sago has been conducted to obtain information on its distribution and habitat conditions. Letsoin et al. (2020) utilized remote sensing data to analyze land cover changes in Merauke from 1990 to 2019, which have implications for the natural habitat conditions of sago. Furthermore, Dimara et al. (2023) used Landsat 8 imagery to map sago habitats based on biophysical characteristics in the Sentani watershed, whereas Dimara and Auri (2023) integrated Landsat 8, QuickBird, and field surveys to map the distribution of sago habitats in the Yapen Islands. The use of QuickBird with a higher spatial resolution enables a more detailed spatial representation. However, the reviewed literature indicates that sago mapping at the stand and individual levels remains limited. This indicates that developments in sago mapping are marked not only by improvements in data resolution but also by a potential shift in mapping units from habitat and distribution toward stand and individual levels (Table 1).

Table 1. Research focus and variables examined for sago research in Papua

Research focus	Author	Year	Variables examined
Distribution and habitat	Pasolon	2015	Soil, groundwater level, rainfall, temperature, and growing environment conditions
	Letsoin et al.	2020	Land cover, land cover change, and distribution/change of sago habitats
	Azhar et al.	2020	Inundation, leaf gas exchange, photosynthesis, chlorophyll fluorescence, and physiological responses
	Azhar et al.	2021	Drought, leaf gas exchange, photosynthesis, and chlorophyll fluorescence
	Dimara et al.	2023	Habitat type, hydrological conditions, and habitat area/distribution
	Dimara and Auri	2023	Landform, slope gradient, elevation, soil, rainfall, and distance from the coast
Stand structure and productivity	Yamamoto et al.	2020a	Plant age, stem length and diameter, stem weight and volume, harvest stage, and starch productivity
	Yamamoto et al.	2020b	Plant age; leaf and stem characteristics; stem length, weight, and volume; and pith dry weight
	Moeljono et al.	2025	Starch production across varieties/cultivars
	Nurulhaq et al.	2022	Accession, growth characteristics, and starch production
	Azhar et al.	2021	Drought, leaf gas exchange, photosynthesis, and chlorophyll fluorescence
Morphological characteristics	Rembon et al.	2008	Fruit and seed characteristics, fruit and seed size/weight, and reproductive traits
	Pasolon	2015	Spine characteristics and sago types
	Yamamoto et al.	2020a	Stem length and diameter, stem weight and volume, and varietal growth characteristics
	Yamamoto et al.	2020b	Leaf and stem characteristics, plant age, leaf number and size, stem length, diameter, and weight
	Nurulhaq et al.	2022	Spine, stem, leaf, and pith characteristics
Genetic diversity	Abbas et al.	2020a	matK gene, genotype, mutation, deletion, and DNA barcoding
	Abbas et al.	2020b	matK gene, species identification, genetic distance, and phylogeny
	Abbas et al.	2021	nad2 and matK genes, haplotype, mutation, and evolutionary relationships
Starch quality and utilization	Yamamoto et al.	2020a	Starch yield, starch productivity, stem volume and weight, pith dry weight, and plant developmental stage
	Yamamoto et al.	2020b	Plant age, starch yield, stem and pith characteristics, and developmental changes related to starch accumulation
	Moeljono et al.	2025	Starch yield, moisture content, fineness, ash content, acidity, and utilization potential
Remote sensing	Letsoin et al.	2020	Remote sensing imagery, land cover, land cover change, and habitat change
	Dimara et al.	2023	Landsat Landsat 8, supervised classification, overlay, habitat types and distribution
	Dimara and Auri	2023	Landsat 8, QuickBird, multispectral classification, field survey, and habitat distribution

SAGO MAPPING TECHNOLOGY

Remote sensing and geospatial technologies have expanded the capability to characterize and map sago resources at increasingly detailed spatial scales. This development involves not only improvements in spatial and spectral resolution but also changes in mapping units, feature representation, classification methods, and validation approaches. In the context of sago, these advances provide methodological opportunities to progress from habitat and vegetation-cover mapping

toward the identification and characterization of more specific plant objects, including stands and individual crowns.

Mapping object shift

Vegetation mapping has gradually shifted from broad vegetation cover to more specific plant objects. In earlier applications, multispectral imagery, such as Sentinel-2 and Landsat-8, was primarily used to map vegetation classes at the landscape level, whereas multitemporal

imagery enabled the analysis of changes in vegetation cover over time (Saini and Ghosh, 2018; Sari et al., 2021). The subsequent adoption of object-based image analysis (OBIA) expanded the information used for classification by incorporating spectral information, vegetation indices, texture, and geometric characteristics as attributes of image objects rather than individual pixels (Mohammadpour et al., 2022).

In sago mapping, the use of high-resolution Pleiades-1A imagery combined with OBIA has enabled the identification of sago based on spectral, arithmetic, geometric, and textural features (Hidayat et al., 2018). Beyond habitat-level mapping, developments in vegetation mapping have increasingly focused on individual tree species through individual tree crown (ITC) delineation, as demonstrated by Xu et al. (2020). Similarly, Spadaro et al. (2025) applied individual crown segmentation to classify tree species in heterogeneous ecosystems. Although these approaches were not specifically developed for sago, they provide relevant methodological developments for advancing sago mapping toward stand- and individual-plant level identification.

Overall, the mapping objects can be understood as a progression from vegetation cover to image-based plant objects and individual plants or tree crowns. This progression is particularly relevant to sago mapping because identifying the presence of sago within an area does not directly provide information on the number, spatial position, or characteristics of individual sago stands. Consequently, increasing spatial resolution alone is insufficient; it needs to be accompanied by segmentation and classification approaches capable of representing individual plant objects more explicitly.

Technological approaches

In earlier vegetation mapping studies, multispectral satellite imagery, such as Landsat-8 and Sentinel-2, was commonly used to characterize vegetation classes and broad spatial patterns based primarily on spectral information. The use of multitemporal imagery subsequently expanded the analysis by incorporating temporal variation in vegetation conditions, while OBIA further extended the information used for classification by incorporating spectral values, vegetation indices, texture, and geometric characteristics of image objects (Saini and Ghosh, 2018; Sari et al., 2021;

Mohammadpour et al., 2022). These indicate a gradual transition from representing vegetation primarily as spectral classes to characterizing more differentiated spatial objects through the integration of multiple image features.

The increasing demand for detailed information at the plant and object levels has encouraged the use of UAV platforms equipped with multispectral and hyperspectral sensors. Compared with conventional satellite imagery, UAV-based observations can provide finer spatial resolution, whereas multispectral and hyperspectral data provide detailed spectral information for distinguishing vegetation and plant species with similar spectral characteristics. Studies have combined spectral bands and vegetation indices with machine-learning classifiers, including k-nearest neighbors (KNN), support vector machines (SVM), and random forests (RF), to improve plant species discrimination (Musungu et al., 2024). However, the increased volume and dimensionality of these data require appropriate feature transformation and selection. Methods such as MNF, ICA, PCA, GLCM, and feature-selection approaches, including SPA, CARS, and UVE, have therefore been used to transform, extract, and select informative spectral and textural features while reducing redundant variables. These feature-processing approaches are commonly combined with machine-learning classifiers, such as RF, support vector machine (SVM), and KNN, for vegetation and species discrimination (Deng et al., 2024; Hartling et al., 2021; Quan et al., 2023; Wang et al., 2022; Liu et al., 2024).

The diversification of data sources has enabled the integration of spectral and structural information. The combination of hyperspectral data with LiDAR, for example, allows vegetation to be characterized using both detailed spectral properties and three-dimensional structural information. This complementary information can improve the discrimination of vegetation types and species compared to approaches based on a single data source (Quan et al., 2023). Simultaneously, studies using UAV LiDAR indicate that improved classification performance does not necessarily depend on increasingly complex algorithms. Instead, the characteristics of the input data, feature selection, and suitability of the extracted features remain important determinants of classification performance (Airlangga, 2024).

Recent studies have increasingly explored deep learning and semantic segmentation as

alternatives to conventional machine learning approaches. For example, active learning and Attention-CNN have been investigated to improve classification while reducing dependence on large numbers of training samples, whereas MEDA-UNet applies a deep-learning architecture for the segmentation and classification of tree species from multispectral UAV imagery. These approaches indicate a methodological shift from manually designing and selecting combinations of spectral, textural, and geometric features to models capable of learning more complex representations directly from image data (Liu et al., 2026; Miao et al., 2024).

Multispectral UAV imagery combined with photogrammetric products can be used to delineate individual tree crowns before subsequent classification, whereas hyperspectral UAV data can be integrated with feature selection and textural approaches to evaluate the performance of different classifiers, including SVM, RF, and KNN (Spadaro et al., 2025; Liu et al., 2024). These further strengthen the transition from area-based vegetation mapping to object-level and individual-plant characterization.

As mapping approaches have expanded toward species classification and individual object analysis, additional metrics such as precision, recall, F1-score, mean Intersection over Union (mIoU), and mean Average Precision (mAP) have become increasingly relevant. These metrics allow evaluation to extend beyond class-level agreement to include the performance of object detection, classification, and segmentation (Xu et al., 2020; Mohammadpour et al., 2022; Liu et al., 2024; Spadaro et al., 2025).

Overall, the technological approaches of vegetation mapping can be characterized by several interconnected transitions: from satellite multispectral imagery toward higher-resolution UAV and multisensor observations; from predominantly spectral information toward the integration of spectral, textural, and structural features; and from conventional classification toward machine-learning and deep-learning.

Mapping technology and information requirements

Mapping performance depends not only on spatial or spectral resolution and classification accuracy, but also on the correspondence between the mapping objective, mapping unit, and the

information required. Therefore, the selection of data, features, analytical methods, and validation approaches should be guided by the intended spatial information (Airlangga, 2024; Mohammadpour et al., 2022).

Different mapping units represent different types of information in the study. Habitat and vegetation cover mapping can indicate the distribution and extent of sago-related areas, whereas stand- and individual-plant-level mapping can provide more explicit information on plant location, spatial distribution, and structural characteristics. The transition toward finer mapping units involves not only higher spatial resolution but also changes in the information represented through spectral, textural, geometric, and structural features (Hidayat et al., 2018; Xu et al., 2020; Spadaro et al., 2025).

The biological and ecological characteristics of sago, including growth, productivity, and responses to environmental conditions, are primarily identified through field-based observations and cannot always be directly represented by remote sensing data (Azhar et al., 2020; Yamamoto et al., 2020a, 2020b). More informative sago mapping therefore requires relationships between field-based characteristics and spatially observable features, supported by appropriate reference data for validation. This integration is necessary to move beyond mapping sago presence toward a more detailed spatial characterization of sago resources (Table 2).

Fragmentation of sago research in Papua

Research on sago in Papua remains spatially and thematically fragmented. The concentration of studies in Sentani and several other locations suggests that current understanding of sago is largely derived from a limited number of study areas, whereas the diversity of sago environments and resources across Papua is considerably broader (Dimara et al., 2023; Dimara and Auri, 2023; Pasolon, 2015). At the same time, the expansion of research themes from habitat and growth to productivity, morphology, genetics, and starch quality demonstrates that sago is increasingly understood as a resource with interconnected ecological, biological, and utilization dimensions (Abbas et al., 2020; Abbas et al., 2021; Moeliono et al., 2025; Nurulhaq et al., 2022; Yamamoto et al., 2020a, 2020b). However, this diversity of research themes has not yet resulted in an integrated

Table 2. Technological aspects relevant to sago mapping

Author	Year	Data	Processing method	Object focus	Classification	Validation
Deng et al.	2024	UAV multispectral	OBIA, segmentation, feature extraction	Plant type	RF	OA, Kappa
Wang et al.	2022	UAV hyperspectral	MNF, ICA, PCA	Plant type	RF	OA
Saini and Ghosh	2018	Sentinel-2, Landsat-8	GS sharpening	Vegetation type	RF, MLC	OA
Mohammadpour et al.	2022	Sentinel-2A	OBIA, PCA, GLCM, VI	Vegetation type	RF	OA, PA, UA, Kappa
Musungu et al.	2024	UAV multispectral	Spectral bands, SI	10 plant species	KNN, SVM, RF	OA, Kappa
Xu et al.	2020	UAV RGB, MS, DAP	SfM, ITC delineation, feature extraction	Tree species	RF	F1, OA, Kappa
Hartling et al.	2021	UAV MS, HS, LiDAR, TIR	Data fusion, MNF	7 Tree species	RF, SVM	OA, Kappa
Quan et al.	2023	UAV LiDAR, HS	Feature selection, RFE	11 Tree species	RF	OA
Liu et al.	2024	UAV HS	SPA, CARS, UVE, GLCM	Tree species	SVM, RF, KNN	OA
Spadaro et al.	2025	UAV MS, photogrammetry	OBIA, ITC segmentation	Individual tree/shrub	RF	OA
Miao et al.	2024	UAV MS	Active learning, attention mechanism	Vegetation cover	Attention-CNN	Accuracy
Liu et al.	2026	UAV MS	Feature extraction, semantic segmentation	Tree species	MEDA-UNet	mIoU, mAP, F1
Airlangga	2024	UAV LiDAR	Feature engineering	Tree species	LR, SVM, RF, KNN, GB, DT	Accuracy, precision, recall, F1

Note: UAV – unmanned aerial vehicle; MS – multispectral; HS – hyperspectral; LiDAR – light detection and ranging; RGB – red-green-blue; DAP – dense aerial point cloud; OBIA – object-based image analysis; ITC – individual tree crown; RF – random forest; SVM – support vector machine; KNN – k-nearest neighbors; MLC – maximum likelihood classifier; PCA – principal component analysis; MNF – minimum noise fraction; ICA – independent component analysis; GLCM – gray-level co-occurrence matrix; RFE – recursive feature elimination; CNN – convolutional neural network; OA – overall accuracy; PA – producer’s accuracy; UA – user’s accuracy; F1 – F1-score.

understanding of the relationships among habitat characteristics, plant traits, and productivity potential at the regional scale. This condition limits the extent to which findings from individual study locations can be extrapolated to represent sago resources across Papua.

The fragmentation is also reflected in the methodological orientation of previous studies. Research focusing on plant growth, morphology, physiology, productivity, and genetic diversity has generally relied on field-based or laboratory approaches, whereas spatial studies have primarily focused on habitat distribution, land cover, and biophysical characteristics (Abbas et al., 2020; Abbas et al., 2021; Azhar et al., 2020, 2021; Dimara et al., 2023; Dimara and Auri, 2023; Yamamoto et al., 2020a, 2020b). Although these approaches provide valuable information, they have largely developed along separate research pathways. Consequently, information on plant characteristics and productivity is not yet consistently

connected with spatial information on habitat conditions and distribution. An integrated framework that links biological and ecological characteristics with spatial variables is therefore needed to improve the regional understanding of sago resources.

Implications of mapping technology development

These limitations become increasingly important as research needs shift from understanding the characteristics of sago to more detailed spatial mapping. The mapping literature shows that advances in sensor capabilities and classification methods now allow objects previously represented as vegetation cover or habitat to be mapped at the stand and individual-plant levels (Xu et al., 2020; Putra and Wijayanto, 2023; Spadaro et al., 2025). However, this shift in mapping units is not merely a matter of using higher-resolution

imagery or more complex algorithms. Changes in the mapping unit also require corresponding changes in the reference data, spatial feature representation, sampling design, and validation procedures (Mao et al., 2025; Spadaro et al., 2025).

The development of satellite-based multispectral mapping toward UAV, hyperspectral, LiDAR, and integrated multisensor approaches provides greater opportunities to characterize vegetation at finer spatial and structural scales (Hartling et al., 2021; Quan et al., 2023; Xu et al., 2020). However, a higher spatial or spectral resolution does not automatically result in more meaningful sago information. The usefulness of these technologies depends on whether the acquired data can capture characteristics relevant to the biological structure and ecological conditions of sago stands. Similarly, machine-learning and deep-learning methods may improve classification and segmentation capabilities, but their performance remains dependent on the quality and representativeness of training data and the alignment between image resolution and the size and characteristics of the objects being identified (Akhtar et al., 2023; Airangga, 2024; Miao et al., 2024).

Therefore, technological advances in mapping should not be evaluated solely based on improvements in classification accuracy. More importantly, consistency among data characteristics, mapping objects, feature representation, classification algorithms, sampling strategies, and validation procedures must be considered (Mohammadpour et al., 2022; Xu et al., 2020; Spadaro et al., 2025). This is particularly relevant for sago because the transition from habitat-level mapping to stand- and individual-level mapping changes the type of information required from both imagery and reference data. A mapping framework designed for habitat classification, for example, cannot necessarily be directly applied to identify individual sago plants without modifications to object definition, training data, and validation procedures.

Research gaps in sago mapping

The main research gap in sago mapping lies in the weak link between biological and ecological knowledge of sago and the spatial information that can be extracted practically. Characteristics such as plant age, stem structure, crown size, habitat condition, and productivity have been investigated through field-based studies (Azhar et al., 2020, 2021; Nurulhaq et al., 2022;

Yamamoto et al., 2020a, 2020b), but have not yet been consistently translated into spatial predictors for stand-level mapping or estimation of productivity potential. Conversely, existing sago mapping studies tend to focus primarily on habitat distribution and biophysical characteristics rather than consistently relating mapped objects to biological characteristics with ecological or agronomic significance (Dimara et al., 2023; Dimara and Auri, 2023; Hidayat et al., 2018). This disconnect limits the ability of spatial mapping to provide information beyond the presence or distribution of sago palms.

High-resolution or multisensor imagery can support regional habitat screening and stand and crown mapping, whereas machine learning or deep learning methods can support biological classification and delineation of individual plants or stands (Hartling et al., 2021; Quan et al., 2023; Miao et al., 2024; Spadaro et al., 2025). Importantly, independent validation across different habitat conditions and geographic locations is required to assess the transferability and robustness of the resulting models (Mohammadpour et al., 2022; Xu et al., 2020).

CONCLUSIONS

This review shows that sago studies on distribution, habitat, growth, and productivity have expanded toward increasingly diverse areas, including morphological characteristics, genetic diversity, and starch quality and utilization. However, the existing literature remains spatially concentrated in several regions and does not fully represent the diversity of sago resources and environments across Papua. In parallel, sago mapping has progressed from the identification of vegetation cover and habitat toward stand- and individual-plant-level mapping using higher-resolution data and increasingly advanced classification approaches.

The higher data resolution and increasing methodological complexity do not automatically ensure improved mapping performance. Mapping effectiveness is influenced by the availability and representativeness of reference data, the suitability of the mapping unit to the characteristics of the target objects, and the quality of validation procedures. Therefore, the main challenge is not simply the development of more advanced mapping technologies

but the integration of biological and ecological knowledge of sago with spatial information.

Combining preliminary regional-scale habitat assessment with stand and crown mapping, biological classification, and the calibration of productivity indices supports more informative methods for mapping cycads—moving beyond the analysis of habitat distribution toward the identification and characterization of stands and individual plants. It may also provide a stronger basis for understanding the spatial distribution, ecological condition, and potential productivity of sago resources across Papua.

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