Mapping Cropping Intensity Transitions in the Philippines from 2001 to 2024 Using Harmonic Analysis of MODIS NDVI Time Series

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Abstract**:** *This study aims to track and analyze changes in cropping intensity across the Philippines to understand spatial and temporal patterns of agricultural practice. This analysis uses MODIS Terra surface reflectance data from 2001 to 2024 to derive a nationwide NDVI time series. The data were grouped into 3-year periods (e.g. 2001-2003, 2002-2004) to model dominant crop cycle patterns using Harmonic analysis, and a moving maximum filter was applied to enhance the detection of vegetation peaks. The first derivative of the filtered temporal signal was computed, and sequences of zero slope segments were extracted to represent valid crop cycles. Cropping Intensity (CI) was calculated averaging the detected crop cycles per year, resulting in values of 1, 2, or 3 cycles per year. Results show that 63.7% of land remained stable in its cropping intensity (CI), with double cropping (CI2) accounting for nearly half of stable areas. This dominance reflects the country's two main cropping seasons, anchored by rice–maize production systems. Intensification (12.6% of transitions) and de-intensification (12.1%) occurred at nearly equal rates, mainly between CI2 and CI3, while 11.7% of transitions involved exchanges with non-cropland, particularly grassland and wetland. Area-based trends highlight further structural shifts. Single cropping declined by nearly 50% over the 24 years, while double cropping, though reduced by 25% since its early-2000s peak, remained the dominant practice, covering ~70% of total crop area. Triple cropping expanded modestly by ~6%, reflecting gradual intensification in select regions. Comparisons with official data show that satellite-derived crop areas (~5.1 Mha) are consistently lower than reported statistics (~7 Mha), reflecting methodological differences between earth observation and survey-based approaches. The results support the use of remote sensing-derived cropping intensity monitoring as a supplementary tool for assessing agricultural dynamics in the country and its potential in guiding sustainable agricultural planning.*

Keywords: Crop Intensity, Crop Volume, Crop Pattern, MODIS, NDVI

Introduction

The Philippines' total land area of 30 million hectares (Mha) classifies 9.97 Mha of its land as agricultural land, accounting for 9% of the country's Gross Domestic Product (GDP) and employing ~23% of the labor force (Philippine Statistics Authority [PSA] (2024), Ichwandiani & Hassan, 2025; Climate Change Commission, n.d.) and ~75-80% of the country's exports (Dogello & Cagasan, 2021). Agriculture plays a central role not only in economic contribution but also in sustaining rural livelihoods, where about 25-30% of the labor force depend on farming or fisheries as their primary source of income (Food and Agriculture Organization of the United Nations, n.d.-a).

Major crops include rice (palay), corn (maize), coconut, sugarcane, and banana (Food and Agriculture Organization [FAO], n.d.-b). Rice and corn are considered staple cereals, forming the backbone of food security, with rice alone providing nearly 35% of average dietary energy intake (Department of Science and Technology [DOST], 2025). Being a tropical country, there are two growing seasons for rice and corn (cereal crops) in most of the Philippines: wet season from May to October, and dry season from November to April (Lansigan et al., 2000). However, production is highly sensitive to varying weather conditions. Crost et al. (2018) identified that rainfall variability influences growth and yield; rainfall during the dry season is often beneficial for preserving soil moisture, while excessive rainfall during the wet season increases the risk of flooding, damaging standing crops. Similarly, typhoons that frequently occur between June and November can cause significant production losses, underscoring the vulnerability of agriculture to climate extremes (Yumul et al., 2011). From this, it becomes invaluable to identify ideal conditions and cycles of agricultural crops to ensure optimal yields in support of livelihood, economic contribution, and food security.

Cropping intensity is closely related to crop cycles but extends beyond seasonal timing. Dayal (1978) defines it as the ratio of the quantity of inputs applied to a constant land area; Mondal (2015) regards it as a determinant of yield; while Challinor et al. (2015) describe it as one source of scale dependency, where the outcome of analysis shifts depending on whether it is viewed at a per-crop, annual, or multi-year scale. In this study, cropping intensity is considered on both spatial and temporal dimensions. Understanding cropping intensity is essential in evaluating how effectively land is used for food production and how agricultural practices adapt under constraints of land conversion, rising population, and climate variability. It also provides a crucial lens for balancing food production with competing land use demands in a rapidly urbanizing country (Li et al., 2014).

Large-scale analysis of both spatial and temporal scales is possible with remote sensing technology. The MODerate Resolution Imaging Spectroradiometer (MODIS), onboard NASA’s Terra and Aqua satellites, has been widely used for monitoring vegetation dynamics because of its high temporal and moderate spatial resolution (Li et al., 2014). MODIS-derived vegetation indices such as the Enhanced Vegetation Index (EVI) and Normalized Difference

Vegetation Index (NDVI) enable the detection of planting, growth, and harvest cycles, providing a reliable proxy for identifying changes in cropping intensity (Zhong et al., 2019).

This study aims to track and analyze changes in cropping intensity to understand spatial and temporal patterns of agricultural practice with the use of available historical satellite data and remotes sensing analysis, through the analysis of information extracted from crop intensity layers in comparison to the recorded/official estimates of crop area and crop volume focused on the country's major crops (*palay* and maize). Determining these patterns opens an avenue for region-specific crop planning, an opportunity to boost crop production and accommodate the growing needs of the country and provide insight into crop cycle planning to obtain optimal/improved crop yield, supporting policy decisions related to food security, climate adaptation, and land use planning.

Literature Review

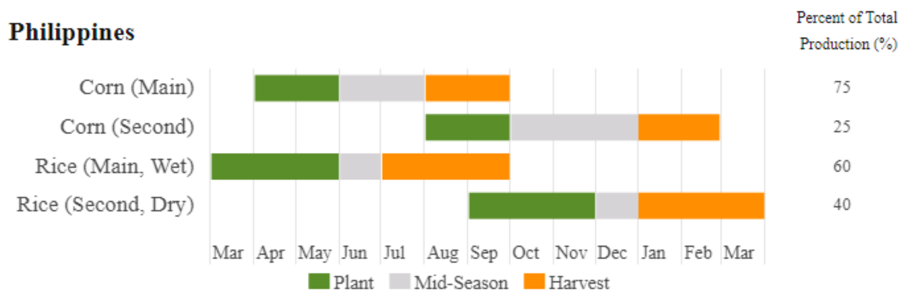
a. Philippine's Current Agricultural Scene: crop calendars and common agricultural practices

Widely recognized as an agricultural country, the Philippines possesses one of the world's most diversified agricultural systems. The Global Environment Facility (GEF) has identified the country as one of only six global priority genetic reserve locations for protecting wild relatives of agricultural crops (Food and Agriculture Organization [FAO], n.d.-b). With farmland ranging from over five million hectares (Balita, 2025), the Philippines cultivates diverse crops influenced by varied climate, unique geography, and distinct regional practices.

Rice and corn remain the dominant staple crops (FAO, n.d.-a), supported by government organizations such as the Philippine Rice Research Institute (PhilRice) and the National Corn and Cassava Program (Department of Agriculture, n.d.). The top five commodities by volume in 2023 were sugarcane, rice (palay), coconut, banana, and corn (Balita, 2025b). Historically, rice occupies 32 percent of agricultural land; coconut, 26 percent; corn, 21 percent; sugarcane, banana, and coffee collectively comprise 8 percent; with the remaining 13 percent distributed among root crops, vegetables, and fruit trees (FAO, 2002). The Department of Agriculture has developed regional crop calendars based on accumulated seasonal and farmer data to guide planting decisions.

Crop calendars provide farmers with essential information to optimize planting schedules (FAO, n.d.-c). Philippine calendars distinguish between wet and dry seasons, with approximately six months of rain from July to October and three months of dry conditions from March to May (Piñol, 2016; Figure 1a). Rice is cultivated year-round, typically planted from December to April during the dry season and from June to October during the wet season (Bordey et al., 2016; Figure 1b). However, localized studies reveal considerable regional variations. Gutierrez et al. (2019) observed that wet season production peaked in June and July, while dry season production peaked in November and December (Figure 1c), demonstrating substantial regional variability in farming practices.

(a)



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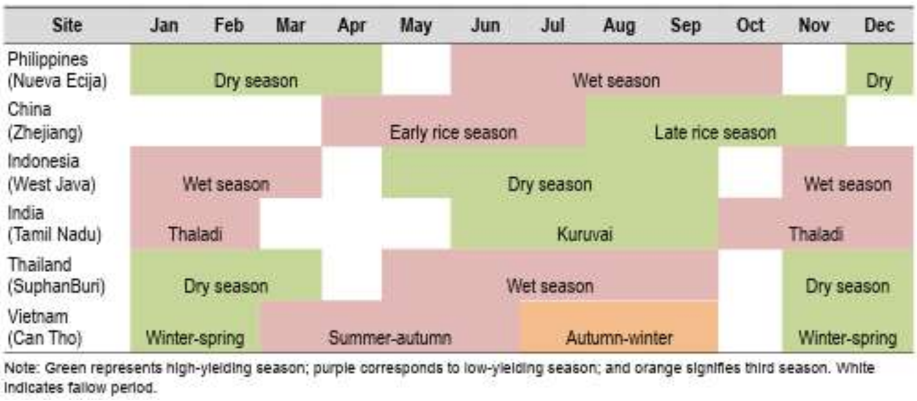

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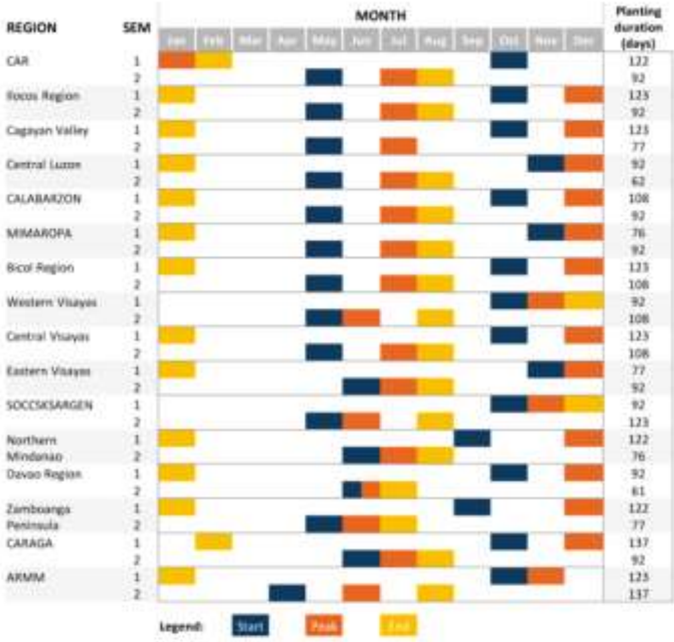

Figure 1. Recorded crop calendars for rice - (a) US-FAS-IPAD (n.d.), (b) Bordey, et al. (2016), (c) Gutierrez, et al. (2019)

No single national crop calendar can be universally applied across the Philippines. Planting and harvesting periods vary due to climatic conditions, particularly frequent typhoons. An average of 20 tropical cyclones enter the Philippine Area of Responsibility (PAR) annually, with 8 to 9 making landfall and significantly impacting agricultural operations (Philippine Atmospheric, Geophysical and Astronomical Services Administration [PAGASA], n.d.). These disturbances cause irregular adherence to recommended crop calendars as farmers adapt to unpredictable conditions through shortened crop cycles, staggered planting patterns, and other strategies.

One notable adaptation is the "double dry" cropping system tested by PhilRice (2025), which enables rice to be harvested twice within a single dry season, increasing production and farmer incomes while reducing vulnerability during years with fewer typhoons. However, adoption has been limited. Silva (2018) identifies constraints including reduced labor productivity, inefficient input utilization, and inadequate access to reliable irrigation—resources that most smallholder farmers lack. These challenges underscore the complex interactions among agricultural management, climate variability, and institutional support, emphasizing the need to deepen understanding of crop cycles and their temporal variations for more robust agricultural decision-making.

b. Efforts on Agricultural Mapping in the Philippines

Most mapping efforts are initiated by the Department of Agriculture and its attached bureaus, either independently or in collaboration with local universities. Both local-scale and large-scale initiatives remain challenging due to extensive ground data requirements and varied methodologies for recording crop areas across seasons, phenological stages, and environmental variables.

Current practices predominantly utilize Remote Sensing (RS) and Geographic Information System (GIS) technologies. Selecting appropriate satellite data based on spatial, temporal, and spectral resolution is critical for specific applications. High temporal resolution imagery from Sentinel-1, Sentinel-2, and Landsat missions have been used extensively to capture seasonal patterns, though with trade-offs in spatial resolution.

Beyond multispectral data, hyperspectral imagery has gained attention for its enhanced capability to discriminate crop conditions, particularly stress and disease detection. The PRISMA and EnMAP missions provide access to hundreds of contiguous spectral bands for retrieving crop biochemical parameters. In the Philippines, Diwa et al. (2024) employed PRISMA data to delineate onion cultivation areas in Bongabon, Nueva Ecija. However, hyperspectral satellites typically offer lower spatial resolution, and high-resolution imagery often requires expensive commercial subscriptions that limit accessibility in developing countries (Govender et al., 2009).

Despite increasing global adoption of remote sensing in precision agriculture, research continues to document persistent difficulties in obtaining accurate, field-level crop maps in the Philippines. Hosonuma et al. (2024) found that flood-prone areas in the Pampanga River Basin experience high inter-annual variability in rice planting opportunities, making consistent phenological patterns difficult to identify. dela Torre et al. (2021) demonstrated how Sentinel-2 NDVI time series can distinguish between irrigated and rain-fed rice systems in Iloilo. Cueto et al. (2024) showed that integrating Sentinel-1 SAR with supervised machine learning in Nueva Ecija successfully differentiated rice from non-rice paddies, though overprediction and misclassification remain considerable challenges.

Institutional challenges also hinder progress. Umali and Exconde (2003) emphasized that lack of inter-agency coordination, data sharing deficits, and technical capacity shortages limit the efficacy of remote sensing and GIS solutions at scale. Wu et al. (2022) noted that limited in situ data, uncertainty during early growth stages, and model transferability issues across regions remain significant obstacles. Local research indicates that while UAVs, spectroscopy, and high-resolution satellite imagery show promise, their broader application is constrained by cost, technical expertise requirements, infrastructure limitations, and phenological complexity (Alberto, 2019).

Efforts at mapping Philippine agriculture have been substantial but remain largely fragmented, localized, and data limited. National initiatives such as the Phil-LiDAR program created agricultural maps using high-resolution imagery and LiDAR-based data (UP DREAM Program, n.d.), while local initiatives by the Department of Agriculture continue. There are also efforts in mapping corn and onion crops by the Philippine Space Agency (PhilSA) in partnership with the Bureau of Agricultural and Fisheries Engineering (DA-BAFE) under the DigitalAgri Phase 1 Project. Additionally, there are ongoing initiatives to integrate the Sen4Stat software algorithms to map major crops across the country. These efforts fall under the Cop Phil Program, which is managed by the European Union Delegation to the Philippines. The program is implemented by the European Space Agency (ESA) in partnership with the Philippine Space Agency (PhilSA) and the Department of Science and Technology (DOST). Despite challenges, diverse research utilizing different resolutions and approaches demonstrates that remote sensing offers valuable information for understanding agricultural dynamics. Enhanced synergy among methods and continued development of localized long-term monitoring systems tailored to Philippine conditions hold significant promise for advancing agricultural mapping in the country.

c. Remote Sensing Techniques in Mapping Crop Intensities

Remote sensing's vital role in crop mapping has been widely used using vegetation index (VI) time series such as NDVI (dela Torre et al., 2021; Oliphant et al, 2019; Dong et al, 2016) and EVI (Eisfelder et al, 2024). These studies have demonstrated that time series analyses are effective in capturing phenological dynamics and aligning them with their corresponding crop calendars. With these published methodologies, subsequent research has shifted towards exploring cropping intensity, which has become more technically feasible.

Analyzing cropping intensities has been a vital part of farm productivity since it enables farmers to engage in rotating crops to ensure soil fertility and minimize diseases and pests. (Ringler, 2024) Particular studies focused on cropping intensity have been accessible. These encompass worldwide detests like the Global Cropping Intensity Dataset (GCI30), providing 30 m resolution maps by means of a phenophase-based approach combining Landsat-8, Sentinel-2, and MODIS imagery. (Zhang et al, 2021)

Concurrent activities in Asia also generated cropping intensity maps. Qiu et al. (2017) created maps of cropping intensity trends in China between 1982–2013 based on MODIS EVI2 (Enhanced Vegetation Index with two bands) time series, detected intervals of decreasing cropping intensity, and showed how these types of analyses can be used to guide effective agricultural policies to stabilize crop yields. In the same vein, Sellaperumal et al. (2025) estimated cropping intensity and pattern in India with MODIS NDVI and Sentinel-1A backscatter; even though the research used third-party software such as TIMESAT for phenology analysis, this points towards a methodology limitation still common in crop mapping. Finally, in Southeast Asia, Ginting et al. (2025) produced cropping intensity maps of rice at 10 m resolution using Sentinel-2 and established the potential of higher-resolution time-series for regional crop monitoring.

Even while such datasets are impressive, they remain constrained by mixed pixels, cloud-masked gaps, and poor ground truthing, which reduce reliability in multi-cropped and heterogeneous landscapes such as the Philippines. Moreover, most global and regional products provide only point-in-time or snapshots for individual years rather than continuous long-term monitoring. These shortcomings highlight the necessity of integrating methodologies that make use of long satellite archives such as MODIS and Landsat to adequately track cropping intensity changes over decades.

Methodology

The approach adopted in this study involved a sequence of steps to generate cropping intensity estimates from temporally dense satellite observations. Daily MODIS surface reflectance data were preprocessed to compute NDVI time series, which were subsequently modeled using harmonic analysis to capture seasonal dynamics. The fitted harmonic curves were enhanced through a moving maximum filter and derivative analysis to identify cropping cycles. These results were then integrated with land cover information to confine cropping intensity values to agricultural areas. Figure 2 provides a schematic overview of the workflow.

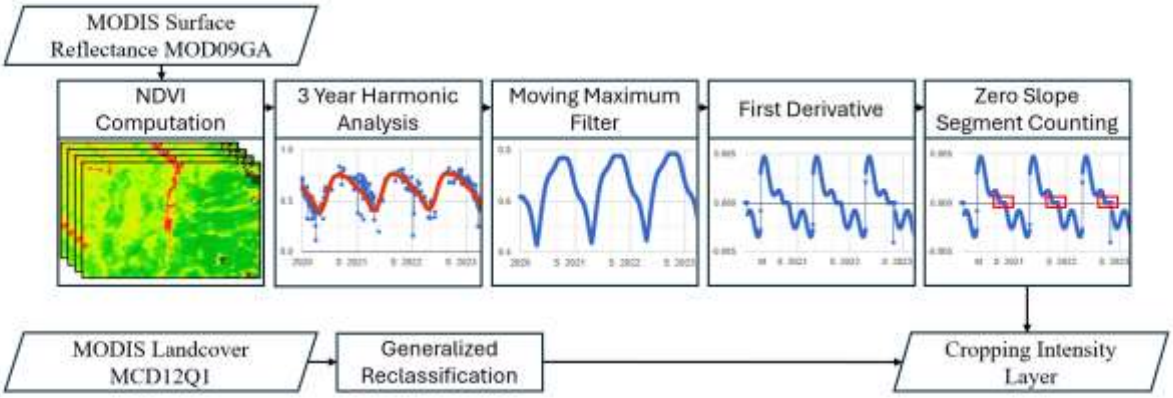

Figure 2: Overview methodology of deriving cropping intensity layers

The in-depth details about the data and each processing step taken to generate the cropping intensity maps are discussed in the following sections.

a. Data

This research used (i) MODIS Terra Surface Reflectance (MOD09GA) daily observations and (ii) MODIS Land Cover Type (MCD12Q1) classified under the International Geosphere-Biosphere Programme (IGBP) scheme. The data were clipped to the Philippine extent for the period 2001–2024. In addition, crop area and volume statistics for palay and maize covering the same period were obtained from the Philippine Statistics Authority's (PSA) OpenSTAT platform. These include estimates of crop production area (PSA, 2025a) and crop production volume (PSA, 2025b), derived from the Palay and Corn Production Survey (PCPS). The PSA datasets were used in parallel with the MODIS observations for the cropping intensity analysis.

b. Surface Reflectance Preprocessing and NDVI

Cloud and low-quality observations were masked using the MOD09GA QA bands. For remaining observations, the Normalized Difference Vegetation Index (NDVI) was computed as:

$$NDVI(t) = \frac{\rho_{NIR}(t) - \rho_{RED}(t)}{\rho_{NIR}(t) + \rho_{RED}(t)}$$

where ρ_{NIR} and ρ_{RED} are surface reflectance values in the near-infrared and red bands, respectively at 500-meter spatial resolution. Daily NDVI within 3 years windows were used for harmonic analysis.

c. Harmonic Analysis

The time series model applied in this research accounts for the long-term trend represented by a linear component and harmonic terms that capture seasonal variability. The regression function is expressed as (Zhu & Woodcock, 2014):

$$\hat{y}(t) = \beta_0 + \beta_1 t + \sum_{k=1}^{K} \left(a_k \cos\left(\frac{2\pi kt}{T}\right) + b_k \sin\left(\frac{2\pi kt}{T}\right) \right)$$

where $\hat{y}(t)$ is the predicted value at time t, T is the mean length of a year in days (T = 365), and β_0 and β_1 are the intercept and slope of the linear component. The coefficients a_k and b_k correspond to the k-th order harmonic terms representing seasonal fluctuations. The maximum frequency order was set to $K = 3$, consistent with the maximum number of observed cropping cycles per year. The fitted harmonic will serve as a smoothened time series for minimizing the error of peak enhancement in the next processing step.

d. Peak Enhancement and Cycle Counting

A moving maximum filter with a 20-day window was applied along the time axis of the fitted harmonic function $\hat{y}(t)$ to transform local peaks into plateau segments:

$$z(t) = \max_{\tau \in W(t,w)} \hat{y}(t), \quad w = 20$$

where $W(t, w)$ denotes the temporal window of length w centered on t. The window size restricts the full expression of plateaus for peaks that are in very close proximity. This will prevent false positive detection of cropping cycles due to complex temporal NDVI trend shapes. The first derivative of the transformed series was then computed as:

$$z'(t) = \frac{dz(t)}{dt}$$

This produced the temporal signal's slope highlighting the presence of flat segments. Zero-slope regions $z'(t) = 0$ correspond to the induced plateaus, which were counted as indicators of cropping cycles. The yearly number of plateau segments in three years was interpreted as the dominant cropping intensity for the time span which ranges from 1 to 3. Iterating the 3-year window processing of harmonic analysis, peak enhancement, and cycle counting from 2001–2024 by shifting one year at a time, produced 22 cropping intensity layers.

e. Land Cover Reclassification and Integration

The method does not account for CI values generated outside areas of agricultural land. To amend this, yearly global landcover (MCD12Q1 IGBP scheme) maps were used to identify regions of agricultural activity. The land cover classes were reclassified into broader categories to reduce noise and improve the interpretability of the change in land cover and cropping dynamics analysis. The corresponding "Agriculture" classes were subsequently replaced by the derived CI values (i.e. 1,2,3). Table 1 summarizes conversion of values from the IGBP scheme to the new proposed classes.

Table 1: Example of a Table Caption

IGBP Code	**Original IGBP Class Name**	**Generalized Class**	**New Code**
1	Evergreen Needleleaf Forests	Forest	11
2	Evergreen Broadleaf Forests	Forest	11
3	Deciduous Needleleaf Forests	Forest	11
4	Deciduous Broadleaf Forests	Forest	11
5	Mixed Forests	Forest	11
6	Closed Shrublands	Shrublands	12
7	Open Shrublands	Shrublands	12
8	Woody Savannas	Savannas	13
9	Savannas	Savannas	13
10	Grasslands	Grasslands	14

11	Permanent Wetlands	Wetlands	15
12	Croplands	Cropping Intensity	1,2,3
13	Urban and Built-up Lands	Built-up	17
14	Cropland/Natural Vegetation Mosaics	Cropping Intensity	1,2,3
15	Permanent Snow and Ice	Permanent Snow	18
16	Barren	Barren	19
17	Water Bodies	Water	20

f. Relating Nationwide Crop Area, Crop Volume to Crop Intensity

Crop Area. The (recorded) crop area from the PSA is subjected to a rolling-average per 3-year interval to make the data compatible with the cropping intensity layers:

$$\bar{x}_t = \frac{x_{t-1} + x_t + x_{t+1}}{3}$$

Where $\bar{x}$ is the rolling average at time t, x_{t-1} is the value from previous year, x_t is the value from the current year, and x_{t+1} is the value from the succeeding year. This produces average crop area values from period 2001-2003, 2002-2004, … to 2022-2024, a total of 22 rows.

The (derived) crop area is extracted from the crop intensity layers by multiplying the total pixel count per class value to the pixel resolution in square meters.

$$Crop\ area = pixel\ count_{class} \times pixel\ resolution$$

Total crop area for single cropping (class value = 1), double cropping (class value = 2), and triple cropping (class value = 3) was calculated, values are represented in the same 3-year period for consistency. The extracted total crop area (derived) was visualized in comparison to the PSA crop area data (recorded).

Crop Volume. PSA's data on major crops volume contains the total value of palay and maize (all crop type, e.g. rainfed palay, yellow corn, etc.). To make the data compatible for comparison with the crop intensity values, a 3-year rolling average from 2001 to 2024 is also calculated. Aside from various statistical tools such as but not limited to mean, standard deviation, and regression for trend analysis, this study will also implement bivariate analysis between the recorded crop volume and derived crop intensity to determine the relationship between the data used. A bivariate choropleth map will also be provided for easier visualization of the behavior of the data in relation to each other. Figure 3 shows the bivariate patterns, where low to high intensity reads from bottom to top, and low to high volume reads from left to right; for example, the upper right corner (H-H) means high intensity and high volume.

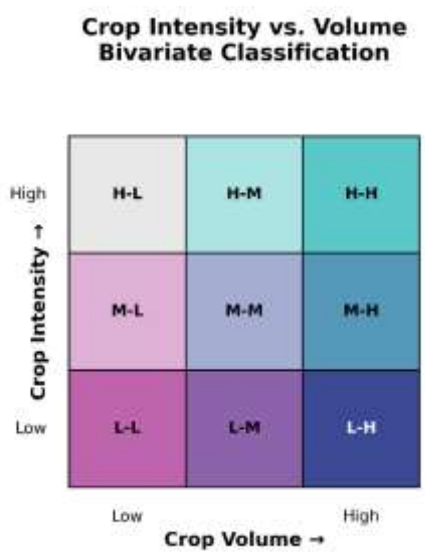

Figure 3. Bivariate Choropleth map legend.

Results and Discussion

a. Crop Intensity and Landcover Transition Patterns

The class transitions of pixels are plotted in an alluvial diagram in Figure 4, which illustrates the flow of land across cropping intensity (CI) classes and non-cropland categories from 2001 to 2024 from the generated Cropping Intensity layers with landcover classes. This visualization captures the direction and magnitude of changes between CI-1 (single cropping), CI-2 (double cropping), CI-3 (triple cropping), and associated landcover classes. Generalized classes that are not directly relevant (i.e. Water, Permanent Snow) or showed no valid pixels (i.e. Barren, Savanna, Shrubland) were not included in the final analysis.

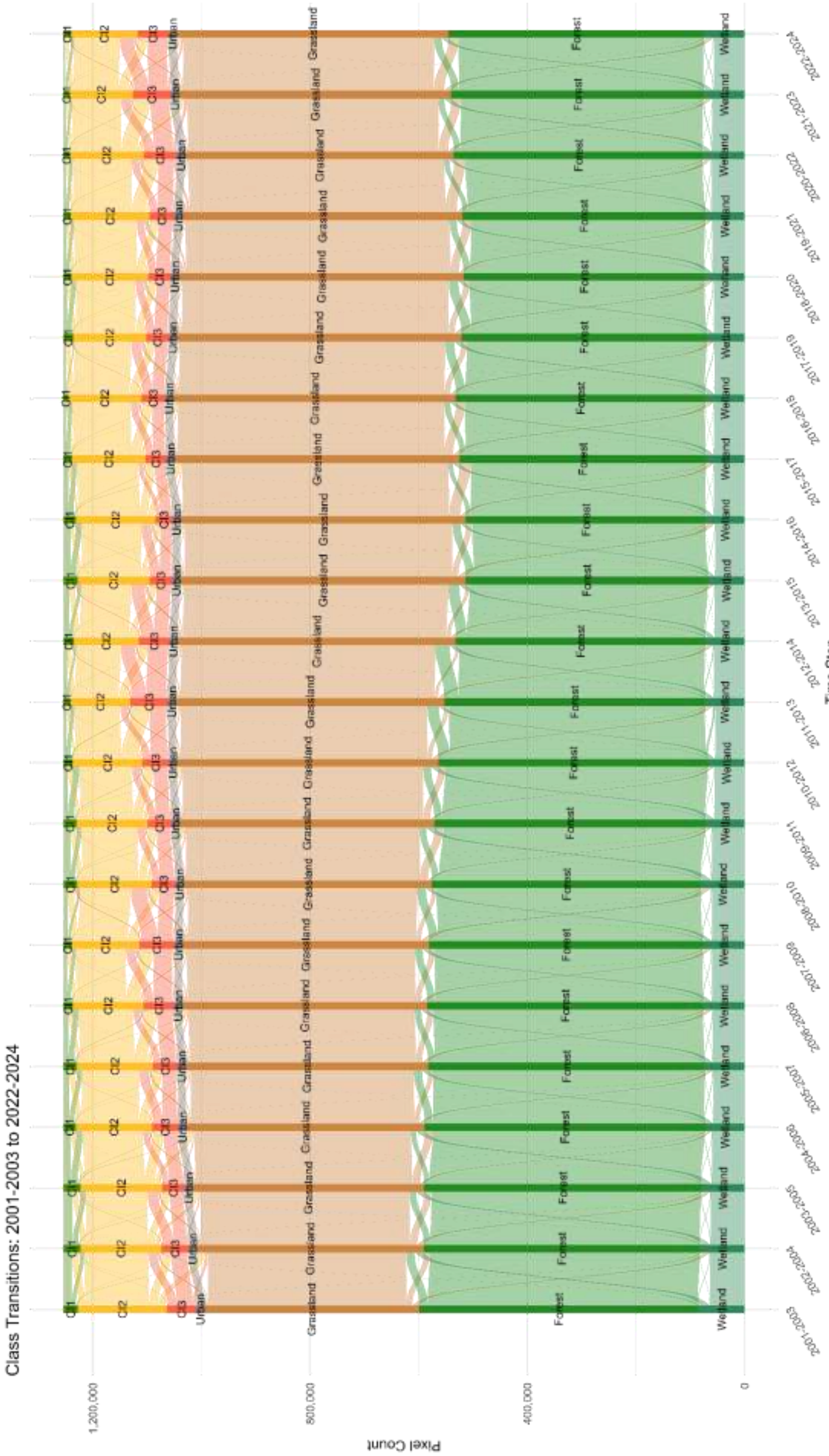

Figure 4. Crop intensity transitions plots from 2001 to 2024.

Across the entire time series, most pixels remained stable in their cropping intensity classification. Approximately 63.7% of all transitions did not change class, amounting to more than ~3.4Mha on average per year. CI-2, corresponding to double-cropping systems, showed the greatest persistence and comprised nearly half of all stable pixels (~2.47Mha km^2 per year). CI-3 stability was lower but still represented a substantial ~0.66Mha per year, while CI-1 accounted for ~0.3Mha of stable land. CI2 comprised most of the stable lands, a pattern that can be explained by the country's two dominant cropping seasons and most produced crops (rice and maize). This reflects the prevalence of double-cropping systems, which remain the most common form of cultivation under prevailing climatic and agricultural conditions. CI-1, or single-cropping systems, accounted for the smallest share of stable lands. This category often corresponds to crops with longer cultivation periods, such as sugarcane, which typically occupy the same field for much of the year and therefore limit the possibility of multiple harvests within a single season.

Although stability dominated, transitions between classes revealed important dynamics. Intensification, defined as movement toward higher CI classes, accounted for 12.6% of all transitions. The most common pathway was CI-2 to CI-3, which alone contributed ~0.44Mha per year on average and represented nearly two-thirds of all intensification. Transitions from CI-1 to CI-2 added ~0.19Mha on average, while rapid shifts from CI-1 to CI-3 were rare, with only ~0.02Mha on average observed.

De-intensification, or shifts toward lower CI classes, was almost equal in magnitude at 12.1% (~0.63Mha per year). Here, most change was CI-3 reverting to CI-2, totaling ~0.43Mha on average. A further ~0.19Mha transitioned from CI-2 to CI-1, while ~0.01Mha on average bypassed directly from CI-3 to CI-1. When the two processes are compared, the net balance favors intensification by only ~0.02Mha, suggesting that the overall cropping system has trended slightly toward higher intensity, but that episodes of intensification and de-intensification largely offset one another over time.

Beyond transitions within CI classes, a significant proportion of land is exchanged between cropland and non-cropland states. Approximately 11.7% of all transitions (~0.64Mha per year) involved these exchanges. Of this, ~0.35Mha on average shifted from cropland to non-cropland, most frequently into grassland (~0.25Mha per year) and to a lesser extent into wetland (~0.09Mha per year). Conversely, ~0.29Mha on average of non-cropland became cropland, again predominantly sourced from grassland (~2.00Mha km² per year) and wetland (~0.87Mha per year). Such transitions may also reflect following practices, temporary flooding or drainage, and other water-related processes that cause cultivated land to alternate with grassland or wetland conditions. The regularity of these shifts across the study period points to seasonal factors, or confusion due to spectral similarity, especially with the coarse resolution of the satellite data used.

b. Derived and Recorded Crop Area

When viewed as absolute crop area rather than transitions, distinct trajectories emerge for each CI class. The highest single cropping area is observed at 0.78Mha. Its highest and lowest crop area values are observed during earlier (2003-2005) and relatively recent (2016-2018) periods (Table 2) with an average of 0.46Mha (±0.17Mha). Single crop area lost 0.0065Mha or ~6500ha annually. In total, single crop areas experienced -48.9% of change in the span of 24 years. On the other hand, double cropping dominates the total crop area throughout the 24-year period, having an average of 3.39Mha (±0.31Mha). Its highest area was observed during 2001-2003 (4.10Mha), and its lowest during 2011-2023 (2.78Mha). In its most recent period, the total area is 3.07Mha, which is 1.03Mha lower than its earlier counterpart or -25.1% cover change, losing ~6400ha (0.006Mha) per year. Lastly, triple cropping area averages at 1.20Mha (±0.25Mha); where it achieved its lowest (0.79Mha) during 2014-2016 and highest (1.74) during 2021-2023. Only triple cropping experienced a relative increase of crop area (5.9%).

Period	Single Cropping (ha)	Double Cropping (ha)	Triple Cropping (ha)	Total Area (ha)
2001-2003	667,725	4,104,850	1,349,025	6,121,600
2002-2004	777,500	3,740,400	1,257,975	5,775,875
2003-2005	779,500	3,763,775	1,050,150	5,593,425
2004-2006	566,650	3,521,100	1,210,700	5,298,450
2005-2007	611,275	3,514,000	1,142,000	5,267,275
2006-2008	430,700	3,256,350	1,421,450	5,108,500
2007-2009	378,825	3,112,475	1,627,925	5,119,225
2008-2010	638,450	3,433,525	1,102,275	5,174,250
2009-2011	598,400	3,291,100	1,093,575	4,983,075

2010-2012	426,125	3,218,675	1,211,700	4,856,500
2011-2013	308,475	2,781,725	1,719,075	4,809,275
2012-2014	465,875	3,008,700	1,413,875	4,888,450
2013-2015	648,000	3,315,400	1,055,450	5,018,850
2014-2016	568,325	3,667,750	789,375	5,025,450
2015-2017	374,825	3,412,475	957,475	4,744,775
2016-2018	211,475	3,385,175	1,093,425	4,690,075
2017-2019	434,800	3,386,425	1,033,200	4,854,425
2018-2020	345,675	3,571,850	1,038,950	4,956,475
2019-2021	325,225	3,648,850	1,137,175	5,111,250
2020-2022	281,400	3,413,625	1,532,250	5,227,275
2021-2023	279,975	2,926,900	1,741,925	4,948,800
2022-2024	341,500	3,074,725	1,428,300	4,844,525
Average	475,486	3,388,630	1,245,784	5,109,900
Std. Dev.	166,751	305,120	253,295	345,658

Table 2. Total cropping area per cropping pattern nationwide for 3-year period from 2001 to 2024 in hectares (ha). Note: Highlighted in red is the lowest value per column, while highlighted in blue is the highest value per column.

Overall, double cropping dominates the crop area scene in the Philippines, comprising of at least 70% of the total crop area throughout the observed periods; followed by triple (~20%) and double (~10%) cropping (Figure 5); this is expected from the country's major crops (rice and maize) which is cultivated bi-annually. Reasons for the decrease and/or increase of the crop area can be transitioning to and from single, double, triple cropping; transformation or conversion to other land use; abandoned land or attributed to the limitations of MODIS Land Classification layers such as misclassification.

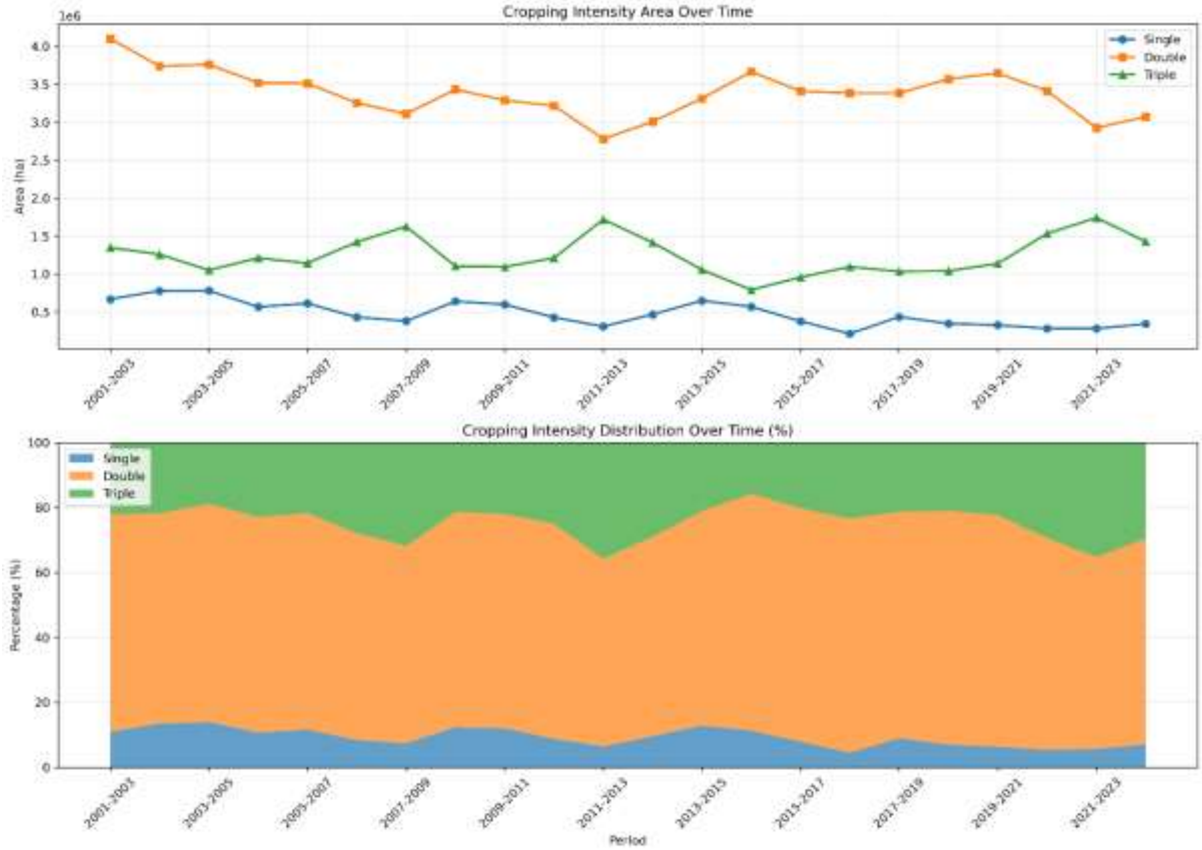

Figure 5. Nationwide Crop Area by Cropping Intensity (2001-2024). Total crop area (top); proportion (bottom).

The derived total crop area average is smaller (5.11Mha) in comparison to the recorded total average (7Mha) (Figure 6). This greatly highlights the differences in results of using different methodologies (remote sensing and statistical survey). The statistical survey employed a two-stage sampling design which accounts for probability proportional to size, potential limitations include sampling and human error, as well as coverage gaps due to outdated sampling frames (PSA, 2023) possibly causing overestimation. While misclassification, limitations for resolution, and mixed pixels, causes underestimation for remote sensing.

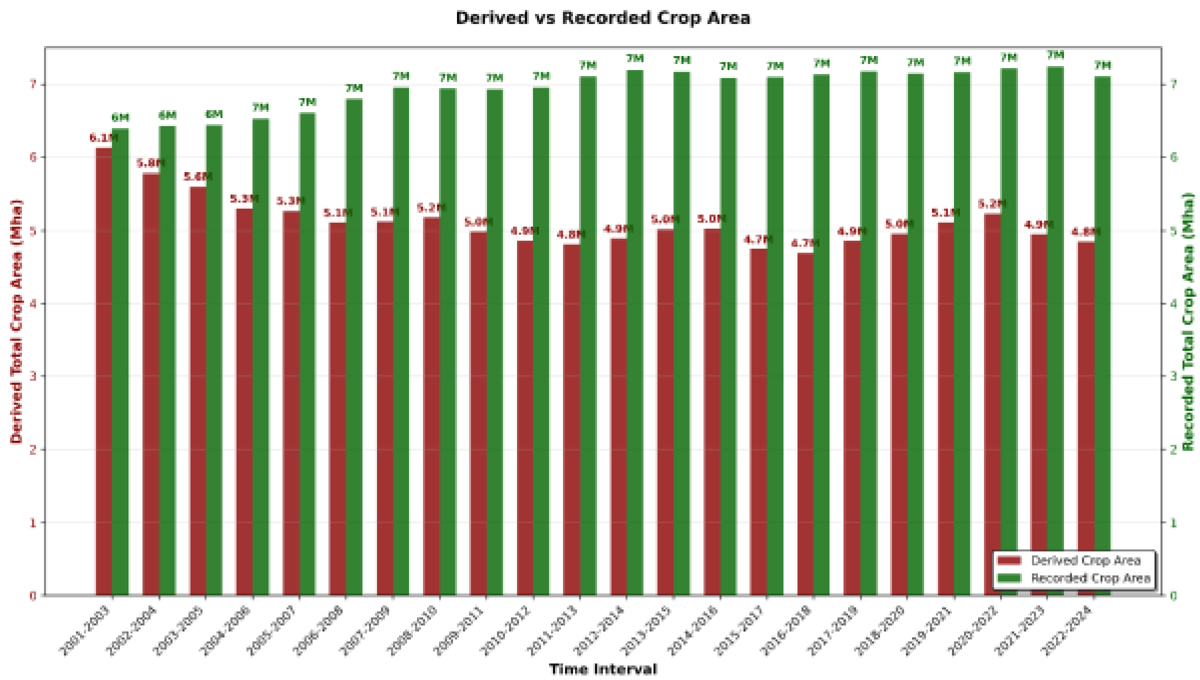

Figure 6. Total derived and recorded crop area from 2001 to 2024 in million hectares (Mha).

c. Derived Crop Area and Crop Volume

Generally, the total crop area derived from the methodology experienced a steep decrease from 2001 to 2007, and in the succeeding years, shows a pattern of highs and lows within the same value range (~4.6Mha to ~5.2Mha). The crop volume (as recorded by PSA), on the other hand, has been increasing consistently (Figure 7). Although this may look like there's an inverse relationship existing between the crop area and crop volume; this implies, instead, that despite having a smaller cropping area, it still produces sufficient or larger crop volume to match the previous periods. To achieve or maintain the increasing trend of crop volume even with lower crop area, these areas must have transitioned from single to double or double to triple crops per year. From 2007 to 2024, peaks and trenches are observable, these fluctuations may be an effect felt from the intensity and number of typhoons that entered the country and had direct impacts on agricultural lands. In 2018, Typhoon Ompong (Mangkhut) caused billion-peso worth of damage to the agriculture sector, majority of which is rice (Simeon, 2018), along with the damage caused by sustained rain from the southeast monsoon (*habagat*). This explains the low value of total crop area during 2016-2018.

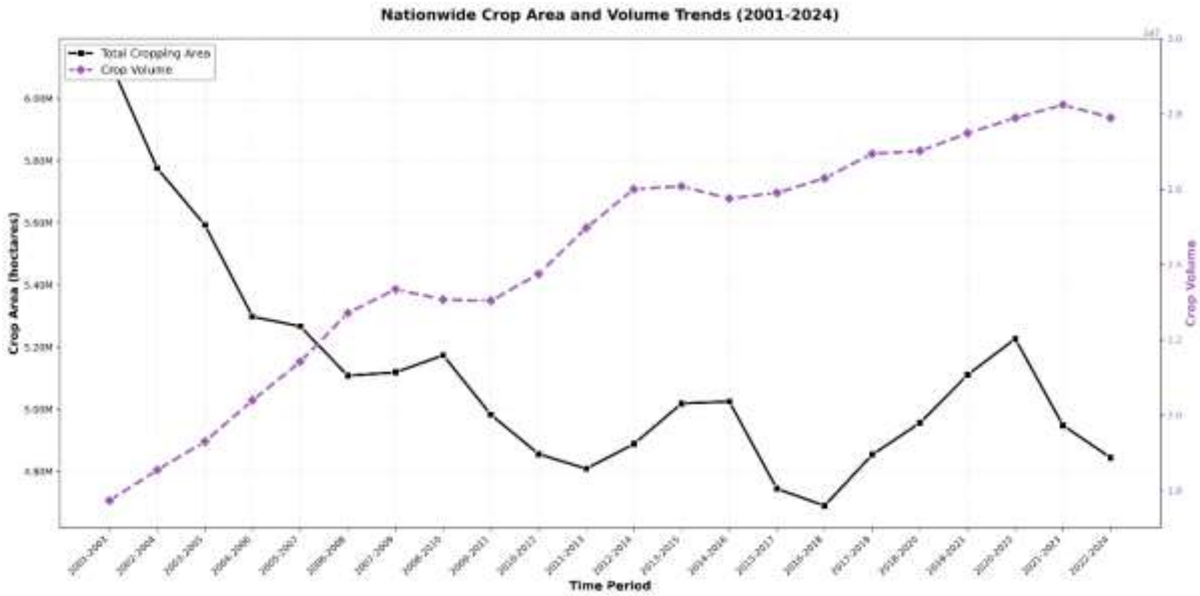

Figure 7. Nationwide total crop area (derived; hectares) and crop volume (metric tons; Philippine Statistics Authority, 2025a).

d. Crop Intensity and Crop Volume

Nationwide average crop intensity and total crop volume shows positive trends and positive correlation (ρ = 0.521). Relationships of these data are best shown during periods 2007-2009 to 2011-2013 and 2012-2014 to 2017-2019 where an observable similar movement in both variables (Figure 8). However, comparing the nationwide values does not provide more information on their relationship. Figure 9 offers a provincial and regional perspective on the behavior of crop intensity and crop volume relative to each other.

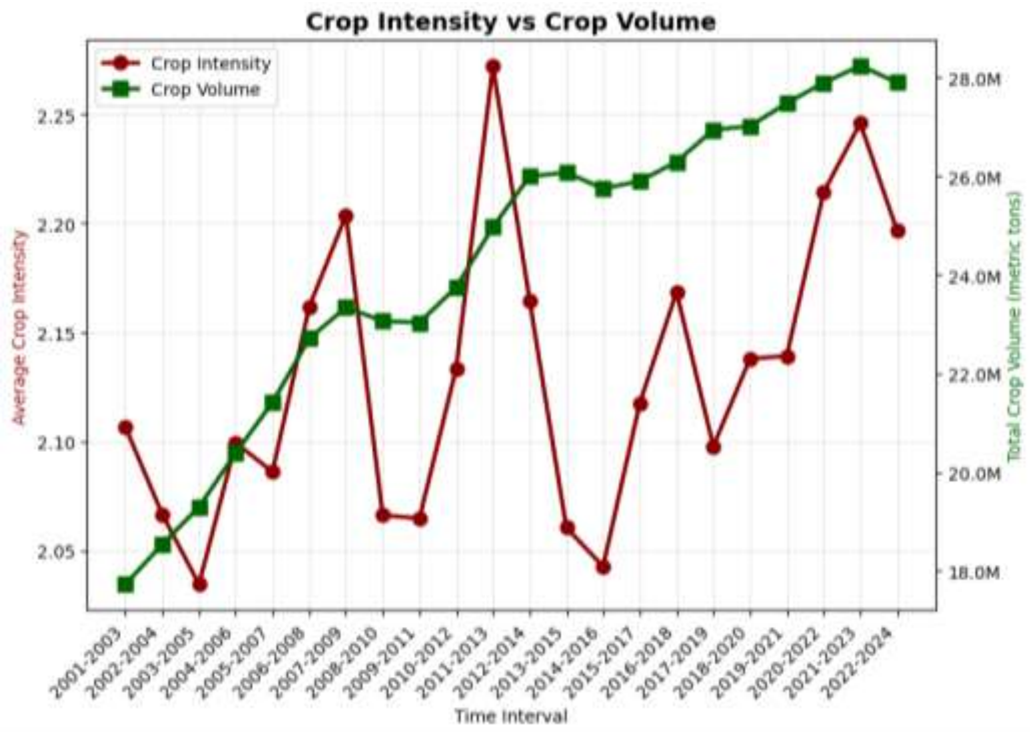

Figure 8. Average nationwide crop volume (*palay* and maize) per year and average nationwide crop intensity every 3-year period from 2001 to 2024 (source: Philippine Statistics Authority, 2025a)

The *High Intensity-High Production (H-H)* type covers Regions I (Ilocos), II (Cagayan Valley), III (Central Luzon), and VI (Western Visayas), which are the country's main rice-producing areas. These regions have extensive lowland plains, irrigated systems, and favorable climatic conditions for intensive rice and corn production, as well as sugarcane and other high-value crops. Central Luzon (Region III) is known as the "Rice Granary of the Philippines" (PhilRice, n.d.), while Cagayan Valley (Region II) supports multiple rice and corn cycles (Regional Development Council – Cagayan Valley Region, 2025). Mature irrigation infrastructure and extensive market linkages enable high cropping intensity and large-scale production, making these regions pivotal for national food security.

The *Low Intensity-High Production (L-H)* type includes Region XII (SOCCSKSARGEN) provinces—North Cotabato, South Cotabato, Sultan Kudarat, and Sarangani—characterized by permanent and export-oriented crops such as banana, coconut, pineapple, rubber, and oil palm (PSA, 2004). These crops yield high production volumes per unit area but are not planted multiple times annually, resulting in low cropping intensity despite substantial output.

The *High Intensity-Low Production (H-L)* category consists of the Cordillera Administrative Region (CAR) and Region IV-A (CALABARZON). In CAR, rugged topography and subdivided farms promote multiple cropping of vegetables, root crops, and rice, but aggregate yields remain low due to slope constraints, soil limitations, and limited mechanization (ATI, 2025). Region IV-A experiences rapid urbanization, particularly in Cavite Province, where agricultural lands are progressively converted to residential, industrial, and commercial uses (Bragais, 2022). While multiple cropping persists on remaining farmland, overall production potential is reduced by spatial limitations and competition with non-agricultural uses, highlighting socio-economic constraints that limit production even under intensive land use.

The *Low Intensity-Low Production (L-L)* category includes Northern Samar (Region VIII), Aurora (Region III), and Surigao del Norte (Region XIII), where agriculture is highly constrained by geographic and climatic conditions. These coastal provinces are vulnerable to typhoons and natural calamities, which inhibit consistent crop cycles and result in low productivity. Livelihoods are often dominated by fishing and coastal resource use, rendering agriculture secondary in these regions.

<table>
<tr><th colspan="2">High intensity, Low production (H-L)</th><th colspan="2">High intensity, High production (H-H)</th></tr>
<tr><td rowspan="2">CAR</td><td rowspan="2">Abra
Apayao
Kalinga
Mountain Province
Ifugao
Benguet</td><td>Region I</td><td>Ilocos Norte
Ilocos Sur</td></tr>
<tr><td>Region II</td><td>Cagayan
Isabela</td></tr>
<tr><td rowspan="2">Region IV-A</td><td rowspan="2">Rizal
Cavite
Laguna
Batangas
Quezon</td><td>Region III</td><td>Tarlac
Nueva Vizcaya
Nueva Ecija</td></tr>
<tr><td>Region VI</td><td>Aklan
Antique
Capiz
Iloilo
Guimaras
Negros Occidental</td></tr>
</table>

Low intensity, Low production (L-L)		**Low intensity, High production (L-H)**	
Region III	Aurora	Region XII	North Cotabato
			South Cotabato
			Sultan Kudarat
Region VIII	Northern Samar		Saranggani
Region XIII	Surigao del Norte		

Table 3. List of Region-Province per bivariate classification of crop intensity vs. production volume in the Philippines (L-L, L-H, H-L, H-H)

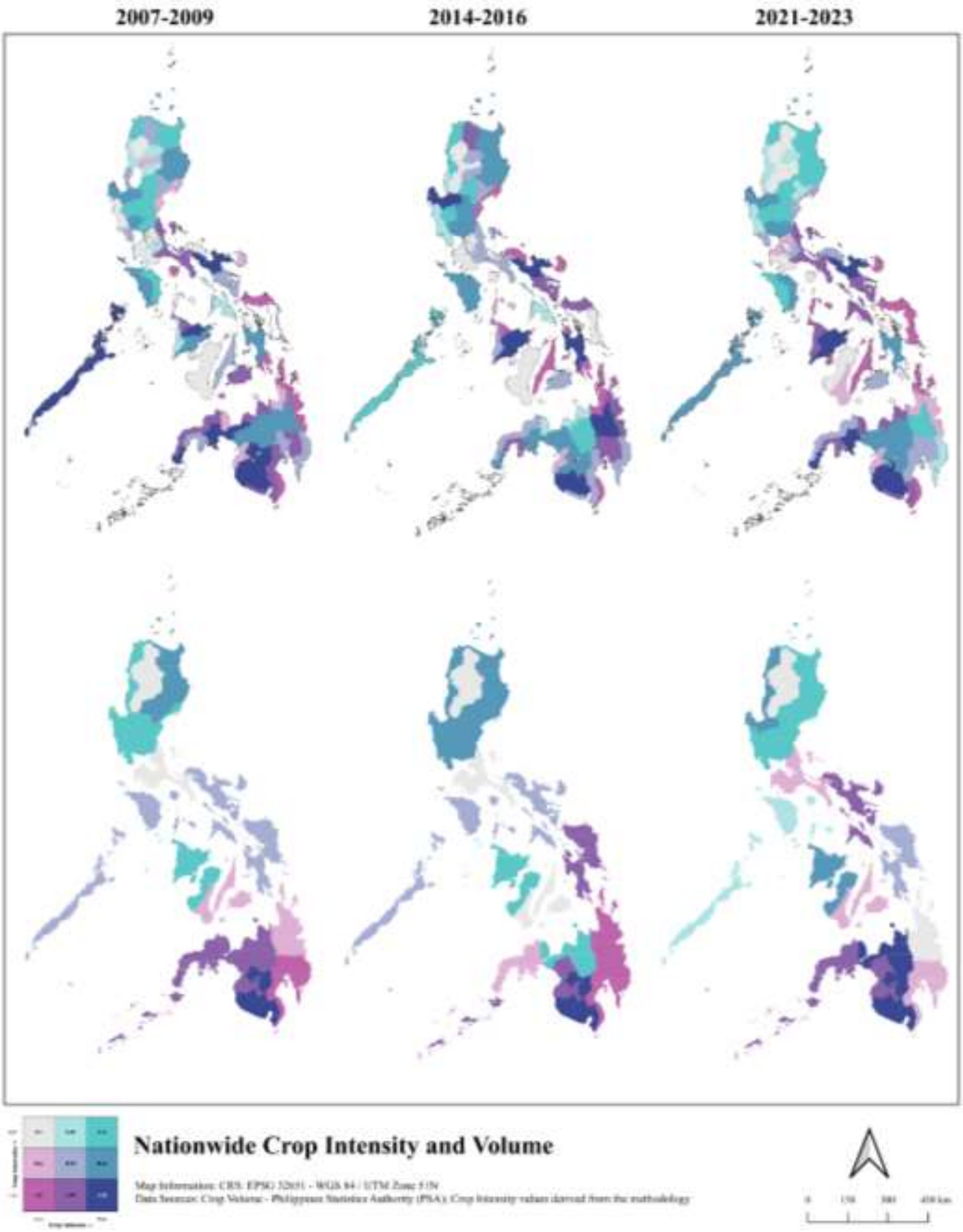

Figure 9. Crop Intensity vs. Production Volume in the Philippines per province (top) and per region (bottom) on selected time intervals.

Conclusion and Recommendation

This research delved into crop intensities and key documented crop figures like area of crops and volume of crop production between the years 2001 to 2024. Results showed that about 63.7% of land remained stable in its cropping intensity classification with double cropping (CI-2) accounting for nearly half of all stable pixels. This confirms the dominance of a stable-double cropping system which correctly aligns with the country's two main cropping systems with rice-maize systems that are prevalent.

Intensification (12.6% of transitions) and de-intensification (12.1%) occurred at nearly equal rates, with shifts primarily between double (CI-2) and triple (CI-3) cropping. Dynamic exchange with non-cropland were also observed with about 11.7% of transitions involved exchanges between cropland and non-cropland (mostly with grassland and wetland). This may suggest seasonal or water-related processes, or a possibility in spectral confusion at coarse-resolution data.

Furthermore, although areas under single cropping have progressively decreased by almost half in the last 24 years, double cropping remains to be the prominent Philippine agricultural landscape, representing approximately ~70% of the entire crop area even with a 25% drop. By contrast, triple cropping increased modestly by ~6%, an indication of changes in cultivation practices. Double cropping is still the dominant trend, with triple and single cropping also being revealed to agree with bi-annual rice and maize cultivation. Such changes may be traced back to changes in cropping intensities, potential land use conversion, land abandonment and constraints inherent on the MODIS-NDVI time-series based classifications. In addition, the crop area derived from space (5.11Mha) is found to be less than reported statistical data (7Mha) as per PSA, and this reflects methodological differences between statistical and earth observation methods that can be due to misclassification, mixed pixels, and geometric errors in remote sensing, as well as bias and overestimation in surveying techniques.

In terms of crop intensity vs. volume production, the categorizations revealed distinct spatial patterns. L-L (low intensity-low production) provinces, which tend to be coastal and subject to typhoons, need risk reduction and livelihood diversification, whereas H-H (high intensity-high production) regions that have uniformly high yields need sustainable intensification. L-H (low intensity-high production) areas that are associated with permanent crops need diversification strategies, and H-L (high intensity-low production) zones influenced by mountainous topography or urbanization emphasize highlight the need for careful land-use planning.

Beyond these recognized spatial patterns, further research should also explore the relationship between crop area, crop intensity and precipitation to better understand climactic drivers that affect productivity. In addition, there is a need for a unified and systematized ground data collection framework that consolidates crop information nationwide, enabling enhancement and validation of current maps to better guide agricultural planning and policy.

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