Title: Catalysing Modernization of Philippine Agricultural Statistics: Integrating Administrative Data, Local Databases, EO, and AI

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Abstract:
Modernizing agricultural statistics has become an imperative as governments confront complex challenges in food security, climate change adaptation, and sustainable rural development. Traditional agricultural censuses, while comprehensive, are costly, increasingly resource- and labor-intensive, infrequent, and may result in significant time lags between data collection and policy application. Fortunately, advances in administrative data, Earth Observation (EO), remote sensing, and artificial intelligence (AI) continue to offer transformative opportunities to re-engineer agricultural data systems. Moreover, it also aligns with global commitments, such as FAO's World Programme for the Census of Agriculture 2030, which emphasizes innovation, flexibility, and the integration of alternative data sources. This paper explores how administrative data, local databases, EO, remote sensing, and AI can catalyse this transformation, with a focus on country experiences and application pathways in the Philippine context.

Administrative records such as farmer registries and beneficiary data offer a continuous foundation but require legal and robust quality frameworks to ensure policy support, government and public cooperation, as well as data coherence and accuracy. Integrating community-level databases into national systems provides finer granularity, while EO and remote sensing contribute objective, spatially explicit insights into crop areas and other land use data. AI and machine learning enhance these processes by automating classification, detecting land-use changes, and enabling predictive yield estimation, provided there is sufficient technical expertise, personnel, satellite imagery, and computing resources.

The results highlight several clear benefits: increased efficiency through reduced census costs, more timely updates, enhanced comparability across diverse landscapes, and stronger, data-driven policy responses to food security and rural development needs.

Modernization of agricultural statistics goes beyond technology. It requires strong institutional commitment, sustained capacity building in geospatial and AI tools, and policy frameworks that seamlessly link local and national databases. By harnessing quality-assured administrative data, scaling up EO and remote sensing, and applying AI-driven analytics, countries can deliver statistics that are timely, relevant, and credible. Success, however, hinges on coordinated action and long-term policy support at the national level.

Keywords: Agricultural Census, Administrative Data, Local Databases, Policy Support, Quality Frameworks, Earth Observation, Remote Sensing, Artificial Intelligence, Modernization

1. Introduction

About 2.33 billion people or 28.9 percent of the global population were moderately or severely food insecure in 2023 according to a report on the world's state of food and nutrition by the Food and Agriculture Organization (FAO) of the United Nations [1]. The reported prevalence of moderate or severe food insecurity, i.e., without regular access to adequate food, for Southeast Asia was at 17.1 percent. Some Asian countries were also reported with the most vulnerabilities to natural disasters based on the 2025 World Risk Index (WRI). In particular, the Philippines have been listed as the most disaster-prone nation among all countries globally since 2022, displacing Vanuatu at the top spot from 2011 to 2021. In 2025, the Philippines scored 46.56, followed by India (40.73) and Indonesia (39.80) [2].

Food security, as a global goal advanced by the FAO, relies on improved agricultural productivity, climate resilience, and sustainable resource management, all of which require informed, evidence-based decision-making. The Philippines' Agriculture and Fisheries Modernization Act (AFMA) of 1997 establishes the country's policy framework for modernizing the agriculture and fisheries sector to enhance productivity, competitiveness, and food security while reducing poverty among farmers and fisherfolk [3]. AFMA mandates the government to ensure food security, defined as the "ability, adequacy, accessibility and affordability of food supplies at all times" through strategic planning, institutional strengthening, infrastructure support, and science- and data-based interventions [3, p.2]. The objectives of AFMA are also closely aligned with the United Nations Sustainable Development Goal (SDG) 2: Zero Hunger, which seeks to end hunger, achieve food security and improved nutrition, and promote sustainable agriculture by 2030 [4]. Achieving these targets requires comprehensive, reliable, and timely agricultural statistics to guide policy formulation and monitor progress.

In this context, the agricultural census serves as a foundational statistical instrument. FAO recognizes the agricultural census as primary source of data for the assessment of food production capacity providing key data on agricultural holdings, land use, livestock, aquaculture, and production systems, forming the benchmark for agricultural statistics systems [5]. Such data are indispensable for evidence-based implementation and monitoring of global and national agricultural policies and programs for specific target groups. The *World Programme for the Census of Agriculture 2020 (WCA 2020)* recommends decennial conduct of agricultural censuses using complete enumeration focused on structural characteristics of agricultural holdings through the classical census approach, modular census approach, or combined modality integrating census operations with administrative and other data sources [5]. These directions are further elaborated in the *WCA 2030, 13th Draft (March 2025)*, which reinforces modular census architecture, interoperability with administrative registers, expanded geospatial integration, and strengthened multi-source data systems, subject to final FAO adoption [6].

In the Philippine context, where the Census of Agriculture and Fisheries (CAF) is implemented by the Philippine Statistics Authority (PSA), these international recommendations provide a methodological basis for assessing the balance between the costly and complex full-field enumeration and the progressive integration of administrative and geospatial data sources.
Agricultural censuses based on complete face-to-face enumeration constitute one of the most resource-intensive statistical operations undertaken by governments. These require large-scale interviewer deployment, logistics coordination across geographically dispersed holdings, and

substantial public expenditure. Population growth, agricultural structural change, and rising labor and transport costs have increased operational complexity and costs. Simultaneously, respondent fatigue, declining response rates, and demand for more timely and diversified statistics in the context of climate change, conflicts, or health emergencies, add pressure on statistical agencies to move beyond purely enumeration-based approaches. Furthermore, falling costs for Earth Observation (EO) data, free Sentinel imagery, improvements in computing and advances in machine learning since the 2010s have accelerated efforts to incorporate remote sensing (RS) and artificial intelligence (AI) into agricultural statistics.

The transformation of agricultural census systems from traditional full enumeration toward combined or register-based models reflects vital shifts in digital governance, administrative integration, and statistical modernization. This paper examines the institutional evolution of these systems and identifies structural determinants shaping the feasibility of hybrid or register-based agricultural statistics, particularly for the Philippines' agricultural census. Moreover, remote sensing, EO, and AI are increasingly used to support, augment, or partially replace traditional agricultural census and survey operations. This paper also scans national trajectories and recent practices across selected countries, describing major transition milestones, key enablers, primary challenges, and pathways for integration into official agricultural statistics. The review draws on FAO program guidance and other technical sources to highlight how a combination of free medium-resolution satellites, national farm-mapping initiatives, and machine learning have shaped census modernization efforts [1].

2. Drivers and Enablers of Transition to Hybrid and Register-Based Agricultural Census Systems: Country Experiences

2.1 The Nordic Transition: Register-Dominant Systems

Since the 1960s, Denmark, Finland, Norway, and Sweden pioneered the statistical use of administrative registers, initially for population censuses, supported by universal personal identification systems and interconnected civil, business, and land registers. By the 1980s, legislation formally authorized national statistical offices to reuse administrative data, enabling systematic linkage of farm, tax, land parcel, and livestock registers for agricultural statistics [7-11]. A major shift occurred under the EU Common Agricultural Policy, particularly the Integrated Administration and Control System, which required geo-referenced parcel declarations and annual crop reporting, effectively creating comprehensive agricultural registers. By the 2000s, core variables such as farm counts, utilized agricultural area, and livestock inventories were largely derived from administrative sources. Agricultural censuses consequently evolved from mass enumeration exercises into data integration and validation systems built on long-standing register infrastructures.

2.2. Australia's Business-Register–Centered Evolution

Australia followed a distinct pathway shaped by its large-scale agricultural structure, with 387.3 million hectares recorded in 2020–2021 [12]. While historically reliant on periodic agricultural censuses, the Australian Bureau of Statistics (ABS) progressively integrated taxation and business registers as part of statistical modernization reforms. Central to this system is the Australian Business Register, which assigns unique Australian Business Numbers and underpins the ABS

Business Register—the principal sampling frame for business and agricultural collections, including the 2020–2021 Agricultural Census.

The high commercialization and corporatization of Australian agriculture, with many farms operating as registered enterprises, has strengthened business register coverage and facilitated the use of register-based frames in agricultural statistics [13].

These Nordic countries and Australia, which represent high administrative maturity environments, provide instructive examples of gradual institutional transformation rather than abrupt methodological reform. Their experiences demonstrate transition to register-based agricultural statistics emerging from strong administrative, legal, and digital ecosystems rather than from statistical innovation alone.

2.3. Japan and Republic of Korea (South Korea): Register-Supported Census Systems

Japan: Register-Supported Census Model with Structural Constraints
Japan has increasingly strengthened administrative support for agricultural statistics through successive Census of Agriculture and Forestry rounds, most recently in 2020 [14]. The census is conducted every five years by the Ministry of Agriculture, Forestry and Fisheries (MAFF), which maintains detailed farm management entity registries, agricultural land use records, and structural farm classification systems.

Since the early 2000s, Japan has enhanced its agricultural statistical infrastructure through the development of farm management entity databases and integration of land information systems under the Agricultural Land Act reforms. However, full administrative substitution remains constrained by structural characteristics of Japanese agriculture. These include: a) high farm fragmentation, b) aging and part-time farm operators, c) complex tenancy and land-use arrangements, and d) significant prevalence of small-scale family farms. As a result, enumeration remains central to Japan's census methodology, although administrative data increasingly support frame construction, cross-validation, and non-response adjustment. Japan therefore represents a register-supported census model, rather than a fully register-based system.

Republic of Korea (South Korea): Subsidy-Linked and Digitally Integrated Registry Model
Since the 2000s, South Korea has implemented subsidy-linked farm registration, requiring farms to register to access direct payments and agricultural support. This policy has produced continuously updated administrative records covering operators, crop and livestock activities, land use, and program participation. Digital land parcel systems and e-government infrastructure further strengthen registry completeness. Agricultural statistics are compiled by Statistics Korea, which conducted the latest Census of Agriculture, Forestry and Fisheries in 2020 [15]. Compared with Japan, Korea has developed a more integrated administrative architecture anchored on mandatory registration. Important sources include the Farm Management Registration System, Agricultural Direct Payment registries, the Korean Land Information System, livestock traceability systems, and integrated e-government platforms linking land, taxation, and agricultural support databases. Administrative data are used to update census frames, pre-fill selected variables, reduce listing costs, and validate crop and livestock data. However, full census replacement has not occurred.

Structural characteristics such as small, mixed, and evolving household farms still require enumeration-based verification.

The experiences of Japan and South Korea demonstrate that strong administrative infrastructures substantially improve statistical frame quality and reduce census operational costs, particularly when farm registration is mandatory and linked to subsidy eligibility. However, in both countries, fragmented smallholder structures continue to constrain full register substitution, necessitating complementary survey operations. These experiences provide important transition lessons for the Philippines, where farm fragmentation and mixed tenure patterns present similar structural constraints and emphasize requirement for sustained legal, technological, and governance reforms.

2.4. Southeast Asia: Census-Dominant Systems-Incremental Administrative Reinforcement

Thailand: Registration-Supported but Census-Dominant

Thailand's agricultural statistics are compiled by the National Statistical Office, with the most recent Census of Agriculture conducted in 2013. Administrative support is provided through the Farmer Registration System, agricultural subsidy registries, land parcel data, and commodity-specific beneficiary databases. However, farmer registration is largely program-linked rather than universal, and informal tenure arrangements combined with fragmented smallholdings constrain administrative completeness. Administrative data are used primarily for frame updating and validation, while census enumeration remains central. Thailand therefore represents a partial hybrid system [16].

Vietnam: Household-Registration-Supported Census Model

Vietnam's 2016 Rural, Agricultural and Fishery Census was conducted by the General Statistics Office. Administrative sources include commune-level household registration systems, the Land Use Rights Certificate database, agricultural production monitoring systems, and cooperative membership records [17]. Despite substantial land digitization, the predominance of small-scale household farming and mixed subsistence-market production limits registry dominance. Administrative data support pre-listing and validation, but enumeration remains fundamental.

Indonesia: Program-Based Registry with Fragmented Coverage

Indonesia's 2023 Agricultural Census was conducted by Statistics Indonesia. Administrative inputs include the Farmer Card registration system, land parcel databases, agricultural subsidy systems, and livestock identification registries. However, decentralized governance and heterogeneous regional systems limit registry consolidation. Administrative integration is expanding but remains incomplete [18].

The Philippines: Census-Dominant with Emerging Administrative Integration

The Philippines represents a census-dominant agricultural statistical system. Agricultural statistics are primarily generated through the CAF and regular agricultural surveys under the mandate of the Philippine Statistical Act of 2013. The most recent CAF round (2022) remained enumeration-based and relied on extensive household and establishment listing operations for frame construction and data collection, while agricultural and fisheries production statistics are generated through a combination of probability-based sample surveys and compilation of administrative records [19].

This census dependence reflects structural characteristics documented in the 2022 CAF, including highly fragmented landholdings, widespread smallholder and family-operated farms, mixed tenure arrangements, and the absence of a universal, legally mandated farm registration system. These conditions constrain the completeness of administrative sources and limit the feasibility of register substitution. Although administrative systems such as the Registry System for Basic Sectors in Agriculture (RSBSA) are expanding, their systematic updating and integration has yet to be operationalized.

Across Southeast Asia, agricultural statistics are similarly census-based with varying degrees of administrative reinforcement. These regional patterns indicate that register-based transition depends not only on technological capacity but also on agrarian structure, legal mandates, and institutional coherence. Countries that advanced toward registry dominance institutionalized mandatory farm registration, harmonized parcel systems, interoperable identifiers, and strong legal authority for data linkage. In smallholder-dominant systems such as the Philippines, a staged hybrid strategy remains methodologically appropriate.

3. Methodological Framework for a Philippine Hybrid Agricultural Census Transition

A short-term strategy for a hybrid administrative integration for the Philippines would parallel transitional experiences in Japan and South Korea, where administrative registers support but will not fully replace census enumeration. For the long-term strategy toward a progressive registry consolidation, this pathway would require interoperability between Department of Agriculture (DA) registries and the Philippine identification System (PhilSys), harmonized parcel-level digitization with DAR and land registries, consolidated farmer identifiers across DA-attached agencies, mandatory digital reporting for subsidy, insurance, and credit programs, and strengthened legal authority for statistical data linkage. Given the country's smallholder-dominated structure, fragmented administrative landscape, and increase in emerging controlled-environment farm practices, the Philippines' transition to a hybrid agricultural statistical system should follow a progressive integration model.

3.1 Legal and Institutional Framework

The transition toward a hybrid agricultural census system is anchored in the Philippine Statistical Act of 2013 (Republic Act No. 10625), which designates the PSA as the central statistical authority and mandates coordination of statistical activities across government agencies. The integration of administrative data for statistical purposes is legally supported by provisions allowing inter-agency collaboration, subject to confidentiality safeguards.

Personal data processing and record linkage activities comply with the Data Privacy Act of 2012 (RA 10173), which establishes principles of lawful processing, proportionality, purpose limitation, and data security. Unique identifiers may be generated supported by verification with the PhilSys data in adherence to Republic Act No. 11055 and its implementing rules, ensuring that any use of the PhilSys data for statistical purposes complies with privacy requirements. All administrative data integration activities will be undertaken within this legal framework, supported by formal data sharing agreements, privacy impact assessments, and strict statistical confidentiality protocols.

3.2 Development of a Unified Agricultural/Fisheries Statistical Frame

The first operational stage involves construction of a Unified Agricultural/Fisheries Statistical Frame by integrating multiple quality-assessed administrative and registry-based sources. These include DA farmer and fisherfolk registries, agrarian reform beneficiary databases, Land Registration Authority parcel records, fisheries and aquaculture licensing systems, commodity registries, fisherfolk registries, and farmers and fisherfolk enterprise databases (Farmers and Fisherfolk Enterprise Development Information System) among others.

Data preprocessing covers variable harmonization, geographic code alignment, structural validation, and categorical standardization. Record linkage combines deterministic and probabilistic matching using standardized names, demographic and geographic identifiers, parcel numbers, and authorized administrative IDs. Each matched unit receives a unique Agricultural Holding Identification Number to enable de-duplication and longitudinal updates. Outputs include a consolidated holding registry, preliminary farm size classes, and linkage quality indicators.

3.3 Coverage Assessment and Diagnostic Evaluation

Following frame construction, coverage adequacy will be assessed against the most recent CAF and subsequent farm and fisheries list updating statistical activities. This assessment adheres to international standards on administrative data quality. The United Nations Economics Commission for Europe guidance requires structured evaluation of coverage, coherence, and comparability before statistical substitution [20], while the Global Strategy framework assesses non-survey sources against relevance, accuracy, completeness, consistency, and sustainability criteria [21]. Coverage diagnostics include computation of coverage ratios, comparison of farm size distributions, and small-area benchmarking at provincial and barangay levels using harmonized geographic codes.

3.4 Stratified Hybrid Operational Design

The hybrid agricultural census model adopts a stratified, modular, and phased integration approach. Based on coverage diagnostics, holdings may be stratified by land size and registration status. Large and commercial farms (e.g., ≥5 hectares) are treated as administratively dominant and covered primarily through validated registers with targeted verification sampling. Medium-sized farms combine administrative frame coverage with probability sampling and model-based imputation for incomplete variables. Small and subsistence farms, where administrative under-coverage is highest, remain enumeration-based with barangay-assisted listing to ensure completeness.

3.5 Modular Census Architecture

The census instrument will be modularized in line with FAO integrated census–survey principles. Core structural variables (area, crops, livestock) are derived mainly from validated administrative sources. Socioeconomic variables remain survey-based, while production and input variables adopt a mixed strategy incorporating model-assisted estimation and validated remote sensing indicators. This design improves cost-efficiency while preserving statistical coherence.

3.6 Governance, Data Sharing, and Confidentiality

Inter-agency data integration is governed by formal Data Sharing Agreements and strict enforcement of statistical confidentiality under RA 10625 and data protection safeguards under

RA 10173, with compliance to RA 11055 where national identifiers are used. A centralized microdata integration platform supports secure linkage, GIS-based parcel integration, and phased validation. Administrative substitution is permitted only after repeated intercensal validation confirms predefined coverage and bias thresholds, ensuring a controlled and evidence-based transition.

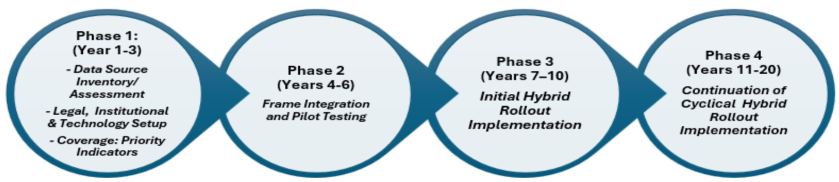
3.7 Technological Infrastructure

Implementation requires a centralized microdata integration platform supporting secure ingestion, probabilistic linkage, automated de-duplication, GIS-based parcel integration, and API-enabled inter-agency data exchange. Machine learning–assisted entity resolution may be used to improve linkage accuracy. Pilot testing in provinces representing commercial, smallholder, and mixed systems will assess scalability, coverage, and cost-efficiency.

3.8 Phased Transition and Validation Strategy

Transition to register-dominant modules follows phased transition as presented in Fig. 1 to ensure statistical continuity, legal compliance, and controlled risk, through a validation strategy in order to confirm predefined coverage thresholds and acceptable bias levels.

Fig.1:
Philippines Phased Hybrid Transition Roadmap



4. Remote Sensing and AI in Agricultural Statistics: Country Experiences

Accelerating EO, remote sensing, and AI tools further support modernization of agricultural statistics. Global experiences provide the methodological and institutional context for the Philippines' proposed hybrid transition, highlighting both the opportunities offered by EO and AI integration and the structural constraints that shape their practical adoption.

4.1 Denmark, Sweden, Norway, Finland

The Nordic region (Denmark, Sweden, Norway, Finland) combines strong national research institutes, public land registers and operational EO groups. Workflows typically use Sentinel-1/-2 time series (10–20 m), Landsat, national aerial imagery and, for targeted tasks, very-high-resolution (VHR) commercial imagery. Common to0ols include local/data-cube deployments, Google Earth Engine (GEE) prototypes, and national decision-support tools such as CropSAT (Sweden). Machine-learning models such as Random Forest (RF) and Support Vector Machine (SVM) and deep-learning (Convolutional Neural Networks (CNNs), time-series networks) are used for crop classification, phenology and yield prediction; research-to-operations links are mediated by national institutes and EU projects (e.g., Sentinels for Common Agricultural Policy) [22].

4.2 Australia

Australia has operationalized EO for agricultural statistics through coordinated work between the ABS and Geoscience Australia, supported by national research partners including the Australian Bureau of Agricultural and Resource Economics and Sciences, and universities. In 2020, ABS and Geoscience Australia conducted a pilot to assess the use of satellite data to improve crop area estimation and agricultural survey design, testing the integration of remotely sensed area estimates with official statistical workflows, reflecting a structured research-to-operations pathway anchored in national geospatial infrastructure. Digital Earth Australia (DEA), a national analysis-ready data cube infrastructure managed by Geoscience Australia, provides standardized Sentinel-1/2 and Landsat time-series data that enable national-scale crop extent mapping and phenology-based monitoring. Machine-learning approaches are implemented through DEA and cloud platforms (e.g., GEE), while hybrid statistical approaches combine EO-derived area estimates with survey totals to comply with official statistics quality requirements [1,24]. The Australian pathway reflects a hybrid adoption model in which EO augments sample surveys.

Japan

Japan integrates EO into agricultural monitoring through collaboration among the MAFF, the Remote Sensing Technology Center of Japan (RESTEC), JAXA-linked programmes, and academic research institutions. RESTEC provides operational remote sensing services for agricultural monitoring, disaster assessment and crop condition analysis. Research initiatives combine Sentinel-1/2, Landsat and domestic radar systems in multi-sensor time-series frameworks. Supervised machine-learning approaches and increasingly deep-learning segmentation methods are applied using agricultural census and administrative parcel data as training labels to produce high-resolution cropland and crop-type maps [25].

Republic of Korea (South Korea)

The Republic of Korea has institutionalized EO integration through the National Farm Map programme led by the Rural Development Administration in coordination with statistical and municipal authorities. The Farm Map provides authoritative geolocated agricultural parcel boundaries and land-use status layers that support subsidy administration, statistical production and policy decision-making.[26] Sentinel-2 imagery and high-resolution data are used for crop classification and Farm Map verification, while UAV imagery enhances delineation of paddy field boundaries. Peer-reviewed research demonstrates the use of machine-learning and deep-learning approaches combining UAV and satellite data to automate field boundary detection and reduce manual digitization.

The Philippines

In the Philippines, EO and AI are increasingly embedded in agricultural statistics and sector modernization. The Philippine Rice Information System produces near-real-time rice area and yield estimates using multi-temporal satellite imagery with field validation, while the Smarter Approaches to Reinvigorate Agriculture as an Industry initiative of the University of the Philippines Los Baños supports crop monitoring, yield forecasting, and early warning through geospatial analytics. The Philippine Space Agency, with DA-BAFE, applies satellite mapping for corn and onion farms [27-29].

Complementing these efforts, the Philippine Statistics Authority's AI4CAF Project (with DOST-ASTI and PhilSA) generated nationwide AI prediction maps for aquaculture structures to support the 2022 CAF, achieving high detection accuracy for fish pens (98.75%) and fishponds (93.64%), with moderate performance for fish cages (84.50%) due to sensor resolution limits. Phase 2 (2025 onward) expands crop and aquaculture mapping using cloud-based platforms (e.g., GEE, Sen4Stat) and AI foundation models such as NASA's Harmonized Landsat–Sentinel-2 models, alongside capacity strengthening under the European Space Agency–supported CopPhil programme to enhance national EO infrastructure for climate and agricultural monitoring.

Country experiences vary but share common tracks. Nordic countries leverage strong national inventory traditions and Sentinel-based research collaborations to support crop and land-use mapping at scale. Australia integrates geospatial visualization within census modernization workflows. Japan demonstrates a research-to-operations pathway supported by remote sensing institutions, while South Korea institutionalizes farm-level spatial registers as inputs to annual statistics. On the other hand, the Philippines' ecosystem is characterized by pilot initiatives, expanding inter-agency collaboration, and increasing institutional recognition of EO as a core tool for smart agriculture and statistical input. However, coordination remains program-based rather than anchored in a legally mandated and nationwide program for geospatial agricultural registry.

5. **Enablers and Challenges**

Thus, key enablers point to: a) strong national policy and program and implementation, b) free, high-frequency satellite data; b) development of farm or parcel registers for spatial linkage; d) scalable cloud-based processing environments; e) high computing infrastructure; and f) strong research–statistics institutional partnerships translating algorithms into operational workflows. However, some challenges persist. Small and fragmented holdings complicate pixel-based classification. Supervised AI requires high-quality ground truth data, which are often costly to obtain. Crop phenology variability limits model transferability across years and geographic levels. Integration into official statistics also requires robust validation, uncertainty quantification, and compliance with legal and privacy frameworks governing administrative data use.

Overall, RS and AI have evolved from experimental tools to operational components of agricultural statistics. Nonetheless, the dominant approach remains hybrid, with technological adoption conditioned by agrarian structure, institutional and information technology capacity, and governance readiness.

6. AI–EO–RS Pathway for Philippines

For the Philippines, a forward-looking AI–EO–RS pathway for agricultural and official statistics modernization can be anchored on the recently launched National Artificial Intelligence Center for Research and Innovation (NAICRI) as the national hub for advanced computing, AI research, and governance. In alignment with the Philippine Development Plan 2023–2028 and the national AI Roadmap led by Philippine Council for Industry, Energy and Emerging Technology Research and Development, the pathway envisions: (i) consolidation of EO and RS data infrastructures, including satellite time series, UAV imagery, and geospatial registries, into interoperable national data platforms; (ii) deployment of AI-enabled crop classification, yield estimation, and land-use change detection models to complement census and administrative registers; (iii) institutionalization of shared high-performance computing and AI governance standards through NAICRI to ensure reproducibility, transparency, and data security; and (iv) phased integration of AI-assisted EO analytics into official statistical production under the leadership of the PSA. This architecture positions the Philippines to transition toward a technology-enabled, hybrid agricultural census and monitoring system, leveraging AI, EO, and RS not as standalone innovations but as core statistical infrastructure supporting evidence-based policymaking, climate resilience analytics, and science-, technology-, and innovation-driven growth.

Conclusion

Production of registry-dominant agricultural statistics is feasible through established national policies toward institutional transformations, spanning decades of progressive cycles with corresponding financial, IT infrastructure, and technical capacity investments. Hybrid models have been useful for countries with constraints in terms of agrarian structures and institutional data fragmentation. In conclusion, international experience from Australia, the Nordic countries (Denmark, Sweden, Norway, Finland), Japan, South Korea, and selected ASEAN countries (Thailand, Malaysia, Vietnam, and Indonesia) confirms that hybrid and registry-based agricultural census models, strengthened by EO, RS, and AI, significantly improve coverage, timeliness, spatial granularity, and cost-efficiency while reducing respondent burden. The integration of administrative registers with satellite time-series and AI-enabled analytics supports smarter agriculture practices and enhances crop and aquafarm area estimation, intercensal updates, with potential data on yield and climate resilience statistics to address worsening environmental and food security issues amid booming population and threats of pandemic or conflicts. Emerging geospatial AI systems, including the NASA–IBM AI foundation models for EO, further demonstrate the potential of large-scale pretrained models to accelerate land cover classification, crop and yield estimation, and anomaly detection within official agricultural statistics frameworks.

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