Mapping and Classification of Crystallization Ponds in Pangasinan Salterns Using LandSat Imagery for Salt Production Estimation

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Abstract. *Crystallization ponds are the final and most essential component of solar salt production systems, where salt precipitates and is harvested after successive evaporation stages. Mapping the spatial extent of these ponds is crucial not only for monitoring salt farm infrastructure but also for estimating potential salt production output. By accurately identifying and delineating crystallization ponds, it becomes possible to project salt yields across wider areas, providing valuable data to support the revitalization and planning of the salt industry throughout the Philippines. This study focused on classifying and mapping crystallization ponds within existing salterns in Pangasinan using remote sensing and GIS-based techniques. LandSat eight (8) satellite imagery was processed using the Supervised Classification tool in ArcGIS to extract crystallization pond features based on their unique spectral characteristics. A refined training dataset enabled distinction from similar land uses such as evaporation ponds, fishponds, and agricultural fields. To evaluate classification accuracy, a total of 151 validation points were collected through extensive ground truthing, including field visits and drone-assisted aerial surveys. Among these, 124 points were correctly classified, resulting in an overall accuracy of 82.12%. This reliable classification demonstrates the potential of integrating remote sensing, GIS, and field validation to generate high-quality spatial datasets. The delineation revealed a total crystallization pond area of 270.74 hectares, with individual pond sizes ranging from 0.18 ha to 36.806 ha. The resulting maps serve as a foundation for estimating salt production potential by correlating pond area with yield estimates. This approach can be scaled nationally, offering a cost-effective method for identifying underutilized salt farming areas and informing data-driven policies for the sustainable development of the salt industry in the Philippines.*

Keywords: *Crystallization Ponds, Geospatial Analysis, Remote Sensing, Salt Production Mapping, Supervised Classification*

Introduction

Salt has been an indispensable commodity for centuries, serving not only as a vital dietary mineral but also as a key ingredient in food preservation, industrial processes, and agricultural applications. In the Philippines, salt production is largely dependent on the solar evaporation method, where seawater passes through a series of ponds until crystallization occurs in the final stage. Among these, crystallization ponds play a critical role as the site where salt precipitates and is harvested. The extent and distribution of these ponds directly influence salt yields, making their identification and monitoring a cornerstone in understanding and managing salt production systems.

Despite its long tradition, the Philippine salt industry has faced significant challenges over the past decades. Domestic salt production has declined due to competition from imports, the conversion of salt farms into other land uses, and limited technological integration in monitoring and planning. Pangasinan, a province historically recognized as one of the country's major salt producers, exemplifies these issues. While vast areas of salterns still exist, there is limited systematic documentation on their present condition and production capacity. This lack of updated and accurate spatial information hampers the industry's ability to assess productivity, plan for revitalization, and develop sustainable management strategies.

Advances in geospatial technologies, particularly remote sensing and Geographic Information Systems (GIS), now provide innovative tools to address these gaps. Satellite imagery provides a cost-effective means of monitoring large areas, while classification techniques enable the differentiation of land cover types based on their spectral signatures. Among these, supervised classification methods have demonstrated strong potential in distinguishing between salt farm components, such as evaporation and crystallization ponds, even when they resemble nearby fishponds or agricultural fields. When combined with ground-truth validation, these methods can generate reliable datasets that support both local and national assessments of the salt industry.

This study explores the application of LandSat 8 imagery and supervised classification techniques in mapping and classifying crystallization ponds in Pangasinan salterns. By accurately delineating pond areas and evaluating classification accuracy through extensive field validation, the research seeks to establish a methodology for estimating potential salt production at the provincial scale. Furthermore, the study demonstrates how integrating remote sensing and GIS can contribute to sustainable resource management, providing policymakers, industry stakeholders, and local communities with data-driven insights to strengthen the Philippine salt industry.

Objectives

The general objective of this study is to map and assess the extent of crystallization ponds in Pangasinan using satellite remote sensing, field validation, and geospatial analysis to estimate potential salt production and provide a scientific basis for revitalizing the local salt industry. Specifically, it aimed to:

1. Map and classify crystallization ponds in Pangasinan salterns using Landsat 8 satellite imagery and supervised classification in ArcGIS.
2. Validate classification results through field verification and drone-assisted aerial surveys to determine accuracy levels.
3. Estimate the total area of crystallization ponds and relate these measurements to potential salt production outputs.
4. Provide a geospatial framework that supports the revitalization, planning, and sustainable management of the Philippine salt industry.

Literature Review

Solar-Evaporation Salterns and the Role of Crystallization Ponds

Solar-evaporation salterns are engineered pond systems that progressively concentrate seawater until sodium chloride (NaCl) precipitates in final-stage crystallization ponds. Because harvestable salt forms in these crystallizers, their area, design (including pond depth and bed material), and operational status determine both the potential yield and the quality of the salt. Loss of pond area, pond fragmentation, or conversion of ponds to other uses (e.g., aquaculture) directly reduces realized production and undermines local livelihood resilience (Montojo et al., 2024). Accurate, spatially explicit inventories of crystallization ponds are therefore critical inputs for revitalization planning.

Remote Sensing Applications in Saltern Mapping

Remote sensing offers a practical and cost-effective approach for mapping salterns and monitoring their extent. Multispectral satellite imagery, such as Landsat and Sentinel-2 has been widely applied to identify salt pans, saline soils, and coastal aquaculture. Bands in the visible, near-infrared (NIR), and shortwave-infrared (SWIR) ranges discriminate exposed saline crusts, brine ponds, and vegetation, while band ratios and indices enhance separation of evaporation ponds from surrounding land covers (Safaee et al., 2020; Yi et al., 2024). Landsat imagery provides multi-decadal, free coverage suitable for provincial-scale monitoring, whereas Sentinel-2 improves resolution and temporal revisit. The integration of optical with radar (e.g., Sentinel-1) further reduces classification errors caused by moisture and illumination variability (AbdelRahman et al., 2022).

Classification Approaches and Methodological Advances

Supervised classification approaches, such as the Maximum Likelihood Classifier (MLC), remain common when representative training samples are available. MLC performs well when class distributions approximate normality and are spectrally separable, but challenges arise in heterogeneous coastal mosaics where ponds, aquaculture, and natural water bodies coexist. Machine learning classifiers, including Random Forests and Support Vector Machines, often outperform parametric methods in these contexts. Recent innovations, such as the Amendatory Saltpan Index (ASI) and hybrid classification approaches that combine pixel-based and object-based analysis, enhance the delineation of irregular pond boundaries (Abuelgasim et al., 2019; Jiao et al., 2023).

UAV and Ground Validation for Accuracy Assessment

Drone and UAV imagery are playing an increasingly important role in the validation and refinement of classification results. Medium-resolution imagery can overlook small ponds or mislabel mixed pixels along pond edges, making high-resolution UAV data crucial for validating classifications, calibrating signatures, and determining operational status (Garrido et al., 2024). Best practices in accuracy assessment include independent validation points, confusion matrices with producers' and users' accuracies, and overall agreement measures.

Production Estimation from Crystallization Pond Areas

Translating mapped crystallization pond area into production estimates requires locally derived yield coefficients (tons per hectare per year) that reflect climate, pond design, and management practices. Empirical approaches include farmer surveys, historical production records, and literature benchmarks. However, uncertainties remain due to inactive or degraded ponds, inter-annual climatic variability, and differences between designed and actual management regimes. Presenting production as a range with explicit assumptions is recommended (Montojo et al., 2024).

Philippine Context and Pangasinan Salterns

In the Philippine context, declining domestic salt self-sufficiency has been linked to climatic constraints, outdated infrastructure, and competition for coastal land use. Pangasinan, once a hub of salt production, has experienced fragmentation of salterns, abandonment of ponds, and conversion to other uses, highlighting the need for updated geospatial inventories (Montojo et al., 2024). Recent initiatives have emphasized modernizing salt production through government-academic partnerships, making validated spatial datasets crucial for prioritizing rehabilitation investments.

Methodology

Study Area

The study was conducted in Pangasinan Province, situated in Northern Luzon, Philippines (Figure 1). Geographically, Pangasinan is bounded by the Lingayen Gulf to the west and the

South China Sea to the north-west, making it highly suitable for salt production due to its broad coastal plains and access to seawater. The province has an elevation range from approximately -5.78 to 1609.17 meters above mean sea level (amsl), encompassing both low-lying coastal areas and upland terrains. These variations in elevation influence land use, with coastal zones being predominantly utilized for aquaculture, fisheries, and salt farming, while higher elevations are devoted to agriculture and settlements.

Pangasinan has historically been recognized as one of the Philippines' major salt-producing provinces, with traditional and modern salterns forming part of the local economy and cultural heritage. Salt production in the area typically relies on solar evaporation methods, with seawater being directed through a series of interconnected ponds—evaporation, concentration, and crystallization ponds—until salt crystals are harvested. The province's climatic conditions, characterized by pronounced wet and dry seasons, also play a critical role in determining the productivity and operational periods of salt farms.

The research specifically concentrated on the coastal municipalities of Dasol, Anda, Bani, Alaminos, and Bolinao. These municipalities host extensive networks of evaporation and crystallization ponds, many of which are actively used, while others have been converted to aquaculture ponds, repurposed for other uses, or abandoned due to economic and environmental pressures. The spatial distribution, transformation, and current extent of these salterns provide a valuable setting for evaluating the capabilities of remote sensing and GIS-based methods in mapping and classification. By focusing on these municipalities, the study highlights the dynamic landscape of salt production in Pangasinan and its potential contribution to national self-sufficiency in salt.

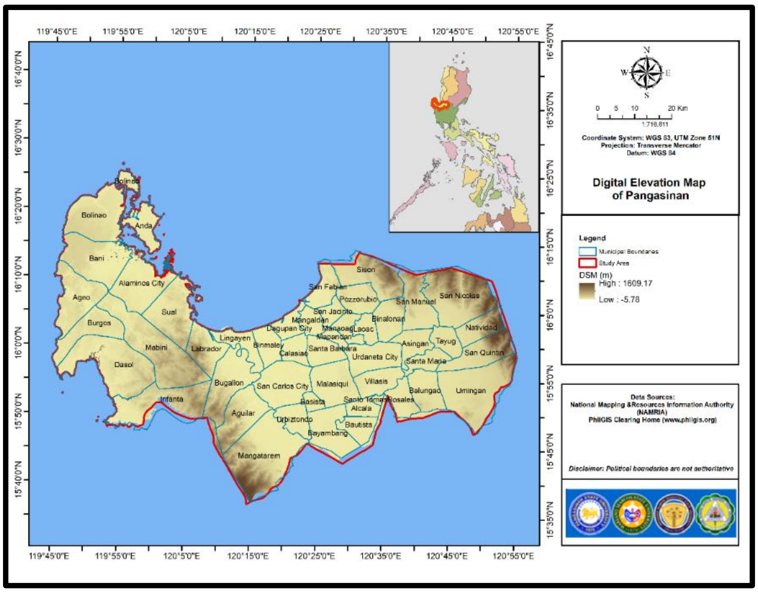

Figure 1. Digital Surface Model Map of Pangasinan.

Data Acquisition

Two primary types of data were utilized in this study: satellite imagery and validation data. The main remote sensing dataset consisted of Landsat 8 Operational Land Imager (OLI) scenes, which provide multispectral imagery with a spatial resolution of 30 meters. These datasets were obtained from the United States Geological Survey (USGS) Earth Explorer platform. To ensure data quality and relevance, only cloud-free imagery corresponding to the dry season months of March to May 2023 was selected. This period was strategically chosen as it coincides with peak salt production activities in Pangasinan, when crystallization ponds are most active and distinctly visible in satellite imagery, while also minimizing atmospheric disturbances such as cloud cover and haze.

In addition to satellite imagery, base maps, and ancillary geographic data were sourced from the Philippine GIS Data Clearinghouse (PhilGIS). These included administrative boundaries, road networks, coastline layers, and hydrologic features, which were used to provide spatial reference, facilitate map overlay operations, and enhance the accuracy of spatial analyses. The integration of PhilGIS base maps with Landsat imagery enabled improved contextual interpretation, ensuring that the delineation and classification of crystallization ponds were anchored to accurate geographic references.

Ground validation data were also gathered through field visits and local knowledge from salt producers, which served as reference points for verifying the classification outputs. These validation datasets ensured that the mapped features accurately represented the actual conditions on the ground, thereby enhancing the reliability of remote sensing–based interpretations.

Through the combination of satellite imagery, PhilGIS base maps, and validation data, a robust dataset was established to support the mapping and classification of crystallization ponds in Pangasinan.

Image Preprocessing

Preprocessing steps were undertaken to prepare the satellite imagery for classification and ensure accurate extraction of crystallization pond features. First, radiometric calibration was applied to convert raw digital numbers (DNs) into top-of-atmosphere reflectance values. This step standardized the imagery, making it comparable across bands and suitable for quantitative analysis. Atmospheric correction was then performed using the Dark Object Subtraction (DOS) method to minimize the effects of scattering and absorption caused by aerosols and atmospheric particles. This correction improved the visibility of surface features, particularly in coastal and near-water environments where haze and atmospheric interference are common.

To enhance feature discrimination, a set of Landsat 8 Operational Land Imager (OLI) spectral bands were selected, specifically the blue (Band 2), green (Band 3), red (Band 4), near-infrared (NIR, Band 5), and shortwave infrared (SWIR, Bands 6 and 7). These bands were combined to generate false-color composites, which accentuated the spectral differences between water-filled crystallization ponds, exposed soil surfaces, and surrounding vegetation. The use of NIR and SWIR bands was particularly important in distinguishing moisture conditions, as well as differentiating shallow water in ponds from saline deposits and dry surfaces.

Subsetting was carried out by applying spatial masks to restrict the imagery to the coastal municipalities of Pangasinan known for saltern activities, including Dasol, Anda, Bani, Alaminos, and Bolinao. This ensured that only saltern-rich zones were retained for further analysis, thereby reducing computational requirements and improving processing efficiency. The combination of corrections, band selection, and spatial subsetting resulted in optimized imagery that provided a clear spectral and spatial basis for subsequent classification and analysis of crystallization ponds.

Supervised Classification

The classification of crystallization ponds was carried out using a supervised classification approach within the ArcGIS environment. This method was selected because it allows the incorporation of prior knowledge about land cover classes, which is essential for distinguishing between spectrally similar features in coastal saltern landscapes.

Training datasets were developed by manually digitizing polygons over representative features, guided by both field survey observations and high-resolution drone imagery. These polygons served as training samples for building spectral signatures that accurately represented the reflectance characteristics of the identified land cover classes. Four primary classes were delineated for analysis: (1) crystallization ponds, (2) evaporation ponds, (3) fishponds, and (4) agricultural land. These classes were chosen based on their spatial prevalence within the study area and their relevance in terms of land use competition and salt production mapping.

Spectral signatures for each class were extracted from the Landsat 8 OLI imagery and used as inputs for classification. The Maximum Likelihood Classifier (MLC) was employed, as it is a widely used parametric method that assumes a normal distribution of class signatures and assigns each pixel to the class with the highest probability of membership. The MLC approach was selected due to its robustness in handling multi-class classification problems and its proven effectiveness in land cover and coastal resource mapping.

Following the initial classification, post-processing procedures were applied to refine the results. A majority filter was implemented to smooth the classified raster, thereby reducing pixel-level noise and minimizing the "salt-and-pepper" effect common in per-pixel classifications. Misclassifications were further corrected by cross-checking outputs with drone imagery and ground validation data collected during field surveys. This iterative validation process ensured greater accuracy in distinguishing crystallization ponds from other similar features, such as aquaculture ponds and waterlogged agricultural plots.

Through the integration of supervised classification, statistical probability-based modeling, and rigorous post-classification refinement, a reliable land cover map of crystallization ponds in Pangasinan was produced. This map served as the foundation for estimating the spatial extent of salt production areas within the province.

Accuracy Assessment

To validate the classification outputs, a combination of high-resolution drone imagery and field-based ground-truthing was employed. Drone surveys were conducted over representative saltern sites within the study area to capture fine-scale imagery of evaporation and crystallization ponds. These drone images provided a detailed visual reference for distinguishing between similar land use features that may be difficult to separate in medium-resolution satellite imagery.

In parallel, a total of 151 ground-truth points were systematically collected during field visits using handheld GPS receivers. These points were distributed across the four major land cover classes considered in the study: crystallization ponds, evaporation ponds, fishponds, and agricultural fields. Care was taken to ensure that validation points captured the heterogeneity of land use types and adequately represented both active and abandoned salterns. This ground reference dataset served as the benchmark against which the classification results were evaluated.

The reliability of the classification results was assessed using a confusion matrix approach, which compared the classified map outputs against the collected validation points. From this matrix, overall accuracy was derived.

By integrating drone-based imagery, ground-truth data, and quantitative accuracy assessment, the study ensured that the classification of crystallization ponds was both reliable and statistically validated, thereby strengthening the credibility of the mapping results for salt production estimation.

Area Calculation and Salt Production Estimation

Following classification validation, the delineated crystallization ponds were extracted as polygon features from the classified raster outputs. These polygons were vectorized in ArcGIS and organized into attribute tables that contain spatial information, such as location, perimeter, and surface area. The Calculate Geometry tool in ArcGIS was then used to compute the total area of each crystallization pond in hectares. This step enabled a precise quantification of the spatial extent of crystallization facilities across the saltern-rich municipalities of Pangasinan.

To contextualize pond areas within the broader salt production system, field surveys and key informant interviews with salt farmers were conducted to establish the ratio of crystallization pond area to total salt farm area. The total salt farm area typically includes evaporation ponds, storage reservoirs, and ancillary facilities, with crystallization ponds occupying only a fraction of the overall production landscape. By applying these ratios, the estimated extent of total salt production areas was derived, thereby linking remotely sensed data with operational farm layouts.

Salt production potential was estimated by correlating crystallization pond area measurements with salt yield values per hectare, which were derived from local benchmarks, farmer surveys, and secondary data sources. These yield factors accounted for variations in production efficiency, seasonal conditions, and management practices across sites. The resulting estimates provided a first-order approximation of potential salt output in each municipality.

This methodology demonstrates how spatial datasets, when integrated with field-derived production benchmarks, can be effectively used to forecast salt production capacity at regional scales. Such an approach underscores the importance of geospatial analysis in monitoring, planning, and supporting the revitalization of the Philippine salt industry.

Mapping and Data Integration

The final outputs of the study were developed into a map and tabulated in summary form. The spatial distribution of crystallization ponds was mapped alongside other land uses, including evaporation ponds, fishponds, and agricultural areas. A GIS database was created to store spatial and attribute data, enabling updates and long-term monitoring of saltern areas. These outputs provide a valuable geospatial framework that can be utilized by industry stakeholders, planners, and policymakers for informed decision-making and the revitalization of the salt industry in Pangasinan and beyond.

Results and Discussion

Classification of Crystallization Ponds

The supervised classification of Landsat 8 imagery successfully delineated crystallization ponds from other land cover types across Pangasinan’s coastal municipalities. Using the Maximum Likelihood Classifier (MLC) and refined training datasets, crystallization ponds were successfully distinguished from visually similar features, such as evaporation ponds, fishponds, and agricultural fields. The classification outputs clearly highlighted the distribution of salt farm infrastructure, particularly in Dasol, Anda, and Bani, where large contiguous saltern complexes are still operational (Figure 2). Smaller and fragmented pond systems were also detected in Alaminos and Bolinao, indicating either abandoned or repurposed salt farms.

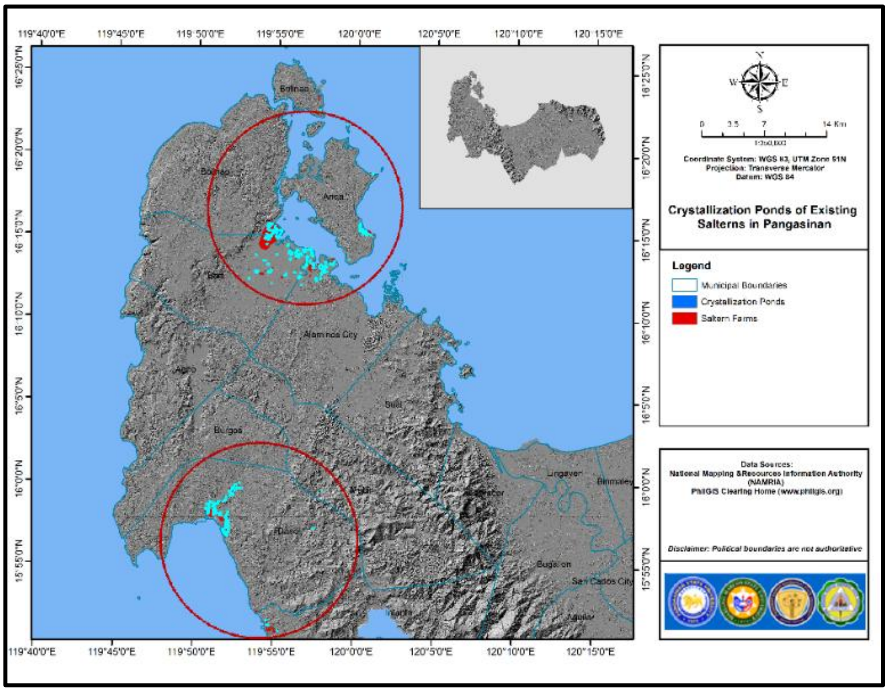

Figure 2. Location of classified crystallization ponds in Pangasinan.

Accuracy Assessment

The accuracy assessment demonstrated that the supervised classification approach achieved a reliable performance in identifying crystallization ponds across Pangasinan. Out of the 151 validation points, 124 were correctly classified, yielding an overall accuracy of 82.12%. This level of accuracy indicates a strong correspondence between the classified outputs and actual ground conditions, confirming the effectiveness of integrating remote sensing, supervised classification, and field validation for saltern mapping.

The user's accuracy was highest for crystallization ponds (salterns), underscoring their distinct spectral properties during the dry season when pond water levels are shallow and salt crystals enhance surface reflectance. Built-up areas were also classified with perfect accuracy (100%), reflecting their well-defined spectral and spatial characteristics. Conversely, lower accuracies were recorded for agricultural land (69.23%) and forest (62.50%), likely due to the presence of mixed pixels at class boundaries and seasonal variations in vegetation.

Notably, misclassifications occurred primarily between evaporation ponds, fishponds, and agricultural fields, where similarities in water depth, turbidity, and surrounding land cover led to spectral overlap. For instance, shallow fishponds under similar management conditions can closely resemble evaporation ponds in spectral reflectance, while waterlogged agricultural plots may be confused with salterns in transitional states. These classification challenges reflect the limitations of medium-resolution Landsat 8 imagery (30 m) in heterogeneous coastal landscapes with small, irregular pond geometries.

Despite these challenges, the achieved accuracy surpasses the widely accepted 80% threshold for land cover classification studies, demonstrating the robustness of the methodology. The results also highlight potential avenues for improving future classifications, such as integrating higher-resolution imagery (e.g., Sentinel-2 or commercial satellites), UAV-derived data, or object-based image analysis (OBIA). These enhancements could reduce spectral confusion, particularly in municipalities where ponds are fragmented or interspersed with aquaculture and agricultural uses.

Overall, the accuracy assessment confirms that the adopted methodology provides a dependable spatial dataset for mapping crystallization ponds, supporting the subsequent steps of salt production estimation and geospatial framework development for industry revitalization.

Table 1. Confusion Matrix

Classification	**Water bodies**	**Forest**	**Agric'l Land**	**Built-up**	**Saltern**	**Total**	**Correct Samples**	**%**
Waterbodies	5	0	1	1	0	7	5	71.43
Forest	0	5	1	2	0	8	5	62.50
Agric'l Land	0	0	9	2	2	13	9	69.23
Built-ups	0	0	0	8	0	8	8	100.00
Saltern	9	1	9	8	124	151	124	82.12
Total	14	6	20	21	126	187	151	80.75

Extent of Crystallization Ponds

The delineation results revealed a total crystallization pond area of 270.74 hectares across Pangasinan. Pond cluster sizes varied substantially, ranging from as small as 0.18 ha to as large as 36.81 ha, reflecting both differences in farm management practices and pond design characteristics. Larger, more contiguous pond clusters were observed in Alaminos, Anda, and Bolinao, municipalities that remain the province's primary salt-producing centers. In contrast, fragmented and smaller ponds were identified in Alaminos, Dasol, and Infanta, indicating reduced salt-farm activity or partial conversion of salterns into aquaculture and agricultural uses. This spatial pattern mirrors the broader decline of the Philippine salt industry, where traditional farms face mounting pressures from land-use changes, competition with more profitable coastal activities, and economic challenges posed by cheaper imported salt. The observed fragmentation and shrinkage of crystallization ponds therefore provide strong spatial evidence of the industry's vulnerability, highlighting priority areas for targeted revitalization and policy intervention.

Table 2. Distribution of crystallization ponds in Pangasinan.

Municipalities	Parcels	Crystallization Pond		
		Minimum Area (ha)	Maximum Area (ha)	Total Area (ha)
Anda	7	0.36	12.03	25.00
Alaminos	28	0.36	8.42	73.08
Bani	11	0.57	11.71	38.97
Bolinao	3	0.54	36.81	50.66
Dasol	68	0.18	7.01	80.99
Infanta	4	0.18	1.32	2.04
TOTAL	**121**	**--**	**--**	**270.74**

Salt Production Estimation

Based on established benchmarks of salt yield per hectare, the delineated crystallization ponds were translated into potential production outputs. Using conservative yield factors, the estimated production capacity from Pangasinan's crystallization ponds ranged in the order of tens of thousands of metric tons annually, depending on efficiency and climatic conditions. While this figure highlights the enduring potential of Pangasinan as a major contributor to domestic salt supply, it also underscores the underutilization of existing saltern areas. Many ponds identified through remote sensing appear inactive or poorly maintained, suggesting that actual production falls significantly below potential. This gap between mapped capacity and realized output reflects systemic challenges, including labor shortages, inadequate capital investment, and a lack of modern production technologies.

Table 3. Estimated salt production of crystallization ponds in Pangasinan.

Municipalities	Total Saltern Area (ha)	Salt Yield (MT/ha/day)	Total Salt Yield (MT/season)
Anda	25.00	14.94	33,620.00
Alaminos	73.08	16.16	106,259.47
Bani	38.97	20.54	72,035.61
Bolinao	50.66	30.53	139,217.20
Dasol	80.99	24.06	175,365.66
Infanta	2.04	28.52	5,236.80
Total	**270.74**	---	**531,734.74**

Implications and Geospatial Framework for Salt Industry Revitalization

The integration of remote sensing, supervised classification, and GIS-based spatial analysis in this study successfully produced a geospatial framework (Figure 3) that can guide the revitalization and sustainable management of the salt industry in Pangasinan. The delineation of crystallization ponds covering 270.74 hectares across six municipalities provides a reliable spatial inventory of active and abandoned salterns. This inventory forms the basis for monitoring infrastructure availability, identifying underutilized areas, and prioritizing rehabilitation projects.

By incorporating both classification accuracy (82.12%) and field validation, the generated maps represent a credible foundation for policy and planning interventions. The geospatial outputs highlight municipalities such as Dasol, Bolinao, and Alaminos as major contributors to potential production, with estimated yields ranging from 33,620 to 175,366 MT per season, depending on site conditions and efficiency. Conversely, fragmented and small-scale ponds in Infanta and Alaminos reflect vulnerability to land-use conversion and reduced productivity.

The GIS database created in this study enables multi-level integration of spatial data—from provincial to municipal and even parcel-level analysis—facilitating monitoring of saltern dynamics over time. This provides stakeholders with a decision-support tool that can:

1. Detect land-use changes, including conversion of ponds to aquaculture or built-up areas.
2. Estimate production potential under different management and climatic scenarios.
3. Identify priority areas for investment, rehabilitation, or modernization (e.g., through pond lining or improved infrastructure).
4. Integrate with socio-economic and climate datasets for long-term planning.

This geospatial framework also demonstrates scalability. With freely available satellite data (Landsat, Sentinel) and complementary UAV surveys, similar methodologies can be applied to other salt-producing regions in the Philippines. Institutionalizing this monitoring framework under government-academic partnerships would enable regular updates, ensuring that production estimates remain aligned with actual pond conditions.

Overall, the results underscore that a geospatially enabled approach is not only a mapping exercise but also a strategic planning tool. By providing reliable spatial information on pond extent, condition, and production potential, this framework equips policymakers and industry stakeholders with actionable insights to reduce dependence on imported salt, optimize land use, and support the livelihoods of salt producers.

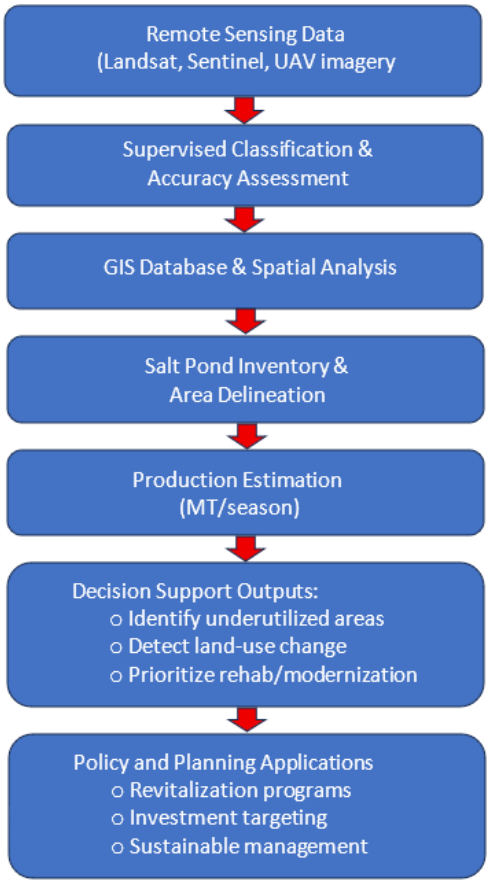

Figure 3. Geospatial Decision Support Framework for Salt Industry Revitalization

Limitations and Future Directions

Despite the success of this study, several limitations should be acknowledged. The 30-meter resolution of Landsat 8 imagery constrained the detection of very small ponds and occasionally caused spectral confusion between adjacent land uses. Incorporating higher-resolution satellite datasets (e.g., Sentinel-2 or commercial imagery) or UAV surveys could improve accuracy in delineating complex pond networks. Additionally, production estimates were based on results of the interview; more precise calculations would require site-specific data on pond depth, brine concentration, and operational practices. Future studies should therefore integrate field-based productivity measurements with spatial datasets to refine yield models and provide more accurate production forecasts.

Conclusion

This study demonstrated the utility of integrating Landsat 8 imagery, supervised classification, UAV validation, and field-based yield estimates for mapping and assessing crystallization ponds in Pangasinan. The approach achieved a reliable classification accuracy, enabling the identification of active and abandoned salterns across the province. Findings revealed that while Pangasinan maintains substantial areas of crystallization ponds, a significant portion of its capacity is underutilized due to fragmentation, pond abandonment, and competing coastal land uses. By linking mapped pond areas with locally derived production coefficients, the study highlighted the discrepancy between potential and realized salt output. The results underscore the need for revitalization strategies that combine spatial data, farmer engagement, and policy support to restore the salt industry's productivity and sustainability. Ultimately, the methodology and findings contribute a replicable framework for regional saltern mapping, which can inform national efforts to reduce reliance on imported salt and strengthen coastal livelihoods.

Recommendations

The findings of this study highlight the urgent need to revitalize and modernize salt production in Pangasinan. To achieve this, government agencies should provide policy and institutional support through financial assistance, technical training, and infrastructure investments for salt producers. Regular monitoring of salterns should be institutionalized using freely available satellite data, such as Landsat and Sentinel-2, complemented by UAV surveys to ensure updated inventories and detect changes in land use. Engaging salt farmers through capacity-building programs that focus on improved pond management, climate-adaptive practices, and yield optimization is crucial to narrowing the gap between potential and realized salt production. Furthermore, the modernization of salt infrastructure, including the rehabilitation of abandoned ponds and the adoption of cost-effective lining materials such as HDPE or improved clay, can enhance salt quality and productivity. Research should also be expanded to integrate high-resolution imagery, climate data, and economic analyses to refine production estimates and evaluate long-term sustainability. Lastly, local governments must incorporate saltern revitalization into coastal land-use planning to balance competing activities such as aquaculture, tourism, and urban development. Implementing these strategies can strengthen salt self-sufficiency, improve local livelihoods, and bolster the resilience of the Philippine salt industry against climatic and economic challenges.

Acknowledgement

The authors extend their heartfelt gratitude to the following people and institutions for their crucial roles in achieving the objectives of this study:

- Project 1 ASIN Staffs'
- Department of Science and Technology
- Philippine Council for Industry, Energy, and Emerging Technology Research and Development (PCIEERD)
- Mariano Marcos State University
- Pangasinan State University – ASIN Center
- Bureau of Fisheries and Aquatic Resources
- Local Government Units of Pangasinan

"Your support and collaboration have been invaluable to the success of this initiative."

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