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Integrated GIS–Socioeconomic Framework for Accelerating Salt Self-Sufficiency in Indonesia

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ABSTRACT

Indonesia’s persistent reliance on maritime salt imports highlights the urgent need for an integrated spatial-socioeconomic framework to accelerate self-sufficiency. This study establishes a data-driven model across ten major salt-producing provinces using 2024/2025 field surveys and 30-meter resolution spatial data. The workflow integrates Geographic Information System (GIS)-based Multi-Criteria Decision Analysis (MCDA), binary logistic regression, and system dynamics (SDs) modeling. Results from the GIS-Analytical Hierarchy Process (AHP) analysis identified 15,500 hectares of highly suitable (S1) land for cluster expansion. Comparative evaluations showed that adopting geomembrane technology significantly increased real productivity from 65.8 to 105.3 tons per hectare per season (95% CI: 33.4-45.6; Cohen’s $d = 2.18$; $p < 0.001$). Furthermore, logistic regression revealed that cooperative membership is the primary determinant of technology adoption, increasing the likelihood more than fourfold (Odds Ratios (OR) = 4.482). Other significant factors included education level and access to extension services. Finally, SDs simulations projected long-term economic impacts up to the 2035 horizon, predicting a 60% to 75% increase in net farmer income. This scalable framework successfully bridges spatial planning and socio-institutional interventions, providing a robust tool for evidence-based policymaking in developing maritime economies.

1. INTRODUCTION

Salt is a strategic commodity driving macroeconomic stability, serving as an essential input for industrial supply chains and human consumption. Despite possessing the world's second-longest coastline and high solar radiation, Indonesia relies heavily on imports to meet domestic demand. This structural deficit drains foreign exchange, exposes industrial sectors to international market shocks, and traps smallholder producers in low-income cycles. The primary bottleneck is the weather-dependent nature of traditional open clay-bed solar evaporation systems, which are highly vulnerable to unpredictable rainfall, wind dynamics, and seasonal shifts, forcing production halts during the wet season [1, 2]. Furthermore, soil contamination causes severe quality degradation, resulting in low sodium chloride (NaCl) purity and high mineral impurities that fail to meet industrial manufacturing standards [3, 4]. Although modernizations like geomembrane linings and greenhouse tunnels improve yields and push NaCl purity above 98%, their adoption remains restricted by high initial capital costs and limited local technical expertise [3, 5].

To guide empirical policy, "salt self-sufficiency" must be operationally defined using quantifiable metrics rather than political rhetoric. Academic literature defines self-sufficiency across three core parameters: aggregate production volume, structural grade differentiation, and the import replacement ratio [6-8]. True self-sufficiency requires system equilibrium across distinct qualitative tiers. A structural paradox exists in developing maritime nations where local farmers generate a surplus of low-grade consumption salt but fail to produce high-purity industrial grades, perpetuating foreign dependence for chemical and food processing industries [7, 8]. This study operationally defines self-sufficiency through a three-pronged threshold: stabilizing total aggregate upstream output, enforcing a strict qualitative baseline of ≥95% NaCl purity to substitute consumption and food industry imports, and achieving a measurable import replacement ratio. Smallholder cooperatives serve as crucial socio-institutional mechanisms to accelerate this transition by operating as open knowledge networks and pooling capital, though their effectiveness depends on local governance maturity [8-10].

Previous strategies have underperformed due to a fragmented policy framework separating biophysical planning from socio-institutional realities. A primary methodological gap is the static application of Geographic Information System (GIS)-based Multi-Criteria Decision Analysis (GIS-MCDA). While spatial models excel at mapping physical land suitability-such as salinity, temperature, and slope [11-13], they treat socioeconomic factors as static, exogenous layers like simple distance buffers [13, 14]. Consequently, they fail to model dynamic feedback loops showing how spatial constraints influence behavioral decisions and technology adoption over time [15, 16]. Conversely, system dynamics (SDs) models simulate long-term policy impacts and adoption pathways but lack high-resolution spatial granularity [16]. Existing frameworks lack an integrated mechanism where empirical micro-level technology adoption probabilities and spatial capacity constraints dynamically feed into a single simulation model. This leaves a clear disconnect between spatial infrastructure investments and the socio-institutional readiness of smallholder communities.

To bridge these gaps, this study develops a unified, data-driven GIS-socioeconomic framework designed to operationalize and accelerate national salt self-sufficiency. The research is guided by three empirical questions: (1) identifying the geographically highly suitable (S1) zones for community-based salt cluster expansion and quantifying their areal extent based on biophysical parameters; (2) determining the magnitude of real productivity gains achieved by transitioning smallholder farms to geomembrane systems after controlling for regional climate variations and farm-level confounding factors; and (3) examining which socio-institutional and demographic variables most strongly influence the probability of geomembrane technology adoption among smallholder salt farmers to accurately calibrate simulation parameters.

Scientifically, this study contributes to the literature on innovation diffusion in developing maritime economies by bridging a critical methodological gap: it operationalizes a dynamic integration framework where static GIS-based spatial suitability constraints directly calibrate micro-level behavioral adoption choices and macro-level SDs simulation parameters. Practically, this framework serves as a scalable decision-support tool for policymakers to accelerate sustainable salt sector transformation; it provides precise geospatial intelligence to optimize infrastructure investments across the identified 15,500 hectares of highly suitable land, while leveraging quantified institutional mechanisms-specifically cooperative membership-to drive zero-waste geomembrane technology adoption, minimize import dependency, and secure national salt self-sufficiency by the 2035 horizon.

2. MATERIAL AND METHODS

2.1 Framework integration architecture

This study establishes a novel hybrid methodological framework that dynamically integrates geospatial suitability, discrete-choice behavioral modeling, and macro-structural simulations. Addressing a major gap identified in the literature regarding the absence of dynamic feedback loops between static spatial constraints and behavioral adoption parameters over time [15, 16], the proposed workflow formalizes a bidirectional input-output data bridge among three analytical components. First, the GIS-MCDA output classified as Highly Suitable (S1) is operationalized as the absolute capacity constraint parameter (Max_Land_{S1}) for the potential land stock variable within the Vensim SDs model. Second, the Binary Logistic Regression results transform empirical Odds Ratios (OR) for cooperative membership (OR = 4.482) and extension access (OR = 2.586) into normalized weighting coefficients (w_i) to calibrate the dynamic Technology Adoption Rate (TAR_t) equation, ensuring that institutional support evolves as an endogenous driver within the simulation framework.

2.2 Study sites and spatial data boundaries

Empirical field data and spatial observations were gathered across the 2024/2025 production cycles, bounding the research scope strictly to ten primary salt-producing provinces in Indonesia: Aceh, DI Yogyakarta, West Java, Central Java, East Java, Bali, West Nusa Tenggara, East Nusa Tenggara, South Sulawesi, and Gorontalo. Spatial data boundaries utilize secondary geospatial layers acquired at a 30-meter pixel resolution, projected using the World Geodetic System 1984 (WGS 84) coordinate reference system. The following are the Biophysical Suitability Criteria and AHP Weights, presented in Table 1.

Table 1. Biophysical suitability criteria and Analytical Hierarchy Process (AHP) weights

Biophysical Criterion	Unit	$S1$ (Highly)	$S2$ (Moderately)	$S3$ (Marginally)	N (Unsuitable)	AHP Weight
Salinity	‰	$3.5-4.5$	$2.5-3.4$	$1.5-2.4$	< 1.5 or > 4.5	0.35
Annual Rainfall	mm/year	$< 1{,}000$	$1{,}000-1{,}500$	$1{,}501-2{,}000$	$> 2{,}000$	0.28
Average Temperature	℃	$28-34$	$25-27$	$22-24$	< 22 or > 34	0.18
Land Slope	%	$0-2$	$3-5$	$6-10$	> 10	0.11
Distance to Coastline	m	$0-500$	$501-1{,}500$	$1{,}501-3{,}000$	$> 3{,}000$	0.08

2.3 Geographic Information System-based Multi-Criteria Decision Analysis

To accurately identify potential zones for economic cluster expansion, we executed a GIS-MCDA utilizing an Analytical Hierarchy Process (AHP) matrix to calculate parameter weights [12, 13]. Biophysical datasets were filtered through explicit threshold classification rules to divide land suitability into four standardized tiers: Highly Suitable ($S1$), Moderately Suitable ($S2$), Marginally Suitable ($S3$), and Unsuitable (N) [17, 18].

The suitability model incorporates five biophysical criteria: salinity, annual rainfall, land slope, distance to the coastline, and average air temperature. We evaluated the pairwise comparison matrices against expert validation protocols, strictly maintaining an AHP Consistency Ratio (CR) below 0.10 to eliminate systematic weighting bias [19]. Final map boundaries and regional acreage totals were calculated using weighted linear combination overlays within QGIS software.

Pairwise comparison matrices were verified against an expert-judgment consensus model, strictly maintaining a CR below 0.10 to eliminate systematic bias. The final suitability map layer was generated via a Weighted Linear Combination (WLC) aggregation overlay, with total spatial geometry area calculations executed within QGIS software.

2.4 Socio-demographic sampling and statistical modeling

Primary socioeconomic data were compiled through a purposive sampling strategy targeting smallholder solar salt farmers across the ten target provinces. To ensure statistical power and modeling precision, we applied a strict data-screening protocol to the field survey pool. Out of 300 original farmer observations, 25 profiles were permanently excluded due to incomplete answers, internal tracking contradictions, or extreme multivariate outliers. This screening process yielded a finalized dataset of 275 valid observations for inferential evaluation.

We constructed a binary logistic regression model to evaluate individual technology adoption decisions, setting geomembrane adoption as the binary dependent variable ($Geomembrane = 1$, $Traditional\ Clay\ Bed = 0$). Predictor variables include farmer age, education level, landholding size, cooperative participation, and access to extension counseling. Model stability was validated using Variance Inflation Factors (VIF), which were restricted below 2.5 to rule out multicollinearity, while overall predictive fit was verified via the Hosmer-Lemeshow test.

2.5 Climate-controlled productivity evaluation

Direct comparative t-tests comparing traditional methods and geomembrane systems face severe confounding risks from multi-provincial climate variations, seasonal lengths, and differing baseline pond layouts. To isolate true technological performance gains from environmental noise, this study replaces simple unstratified testing with a climate-controlled analysis.

We implemented multiple linear regression modeling alongside stratified t-tests to evaluate seasonal productivity (expressed in tons/ha/season). By embedding provincial climate parameters-specifically seasonal rainfall totals and average regional temperatures-alongside operational farm characteristics (such as cultivated land area size) as continuous control variables, the model isolates the net technological impact of geomembranes. Performance gains are reported with 95% confidence intervals (CI) and practical effect sizes (Cohen's d) to ensure mathematical rigor.

2.6 System dynamics simulation setup

To project the long-term macroeconomic impacts of the proposed integrated cluster interventions, we developed a mathematical Stock and Flow simulation model using Vensim PLE software. To resolve the timeline contradictions identified in the original draft text, both the model architecture and all reported simulation outcomes are structurally locked to a uniform, long-term planning horizon spanning from 2025 to 2035. The system boundary coordinates causal loops and dynamic interactions between salt production capacity, technology adoption velocity, cooperative participation rates, market prices, and net smallholder household incomes. The simulation was parameterized using the spatial constraints derived from the GIS-MCDA step and calibrated utilizing the socio-institutional adoption weights generated by the logistic regression model.

3. RESULTS

3.1 Socio-demographic and baseline production profiles

The baseline data highlights several technical and socioeconomic gaps across the sample population. Out of the 300 original respondents, data screening left 275 valid observations for inferential statistical analysis. The descriptive profile shows an experienced but aging workforce, with an average age of 48.5 years and a mean farming experience of 22.3 years.

Table 2. Distribution of highly suitable ($S1$) land for salt clusters

Province	Region Classification	Calculated S1 Area (Hectares)
East Java	Volume-based Cluster	5,200
Central Java	Volume-based Cluster	2,800
East Nusa Tenggara (NTT)	Volume-based Cluster	2,100
South Sulawesi	Volume-based Cluster	1,800
West Java	Volume-based Cluster	1,500
West Nusa Tenggara (NTB)	Volume-based Cluster	1,100
Aceh	Value-based Cluster	400
Gorontalo	Value-based Cluster	300
DI Yogyakarta	Value-based Cluster	150
Bali	Value-based Cluster	150
Total Accumulated Area	National Scale	15,500

Human capital and institutional participation remain low; 70% of the sampled farmers possess a formal education level of junior high school or below, and only 35% hold active memberships in local salt cooperatives. Production plots are relatively fragmented, averaging 1.2 hectares per farm, though a majority (60%) operate on self-owned land. Traditional open clay-bed evaporation methods dominate the landscape at 55%, while modern geomembrane systems account for 37%, and the remaining small fraction utilizes tunnel or salt house technologies that was presented in Figure 1.

3.2 Geospatial land suitability rankings

The GIS-MCDA framework processed the biophysical and environmental criteria layers across the ten designated provinces. Weighted linear combination analysis identified a total aggregate area of 15,500 hectares matching the Highly Suitable ($S1$) classification for future community-based salt economic cluster expansion. Table 2 details the spatial distribution and geometric area calculations across the ten provinces.

The following is a graphic depicting the Geospatial Analysis of Land Suitability for Coastal Salt Clusters (n = 10 Provinces), presented in Figure 2.

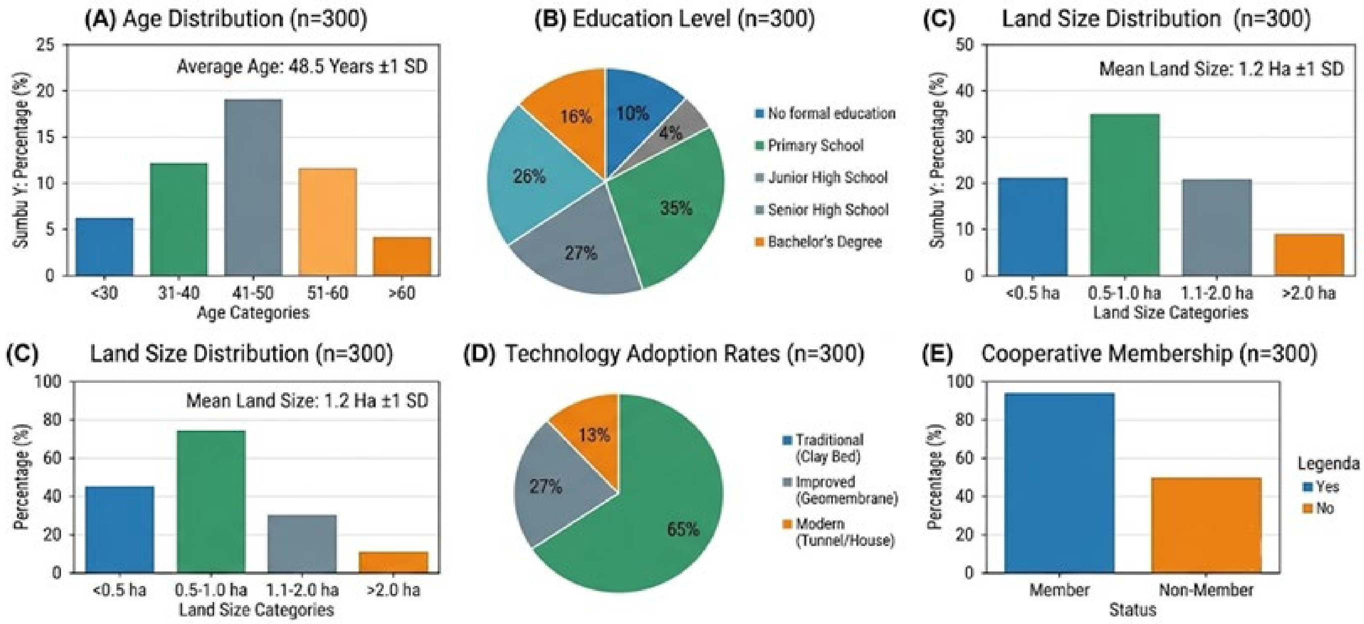

Figure 1. Socio-demographic and technical profile of sample salt farmers (n = 300)

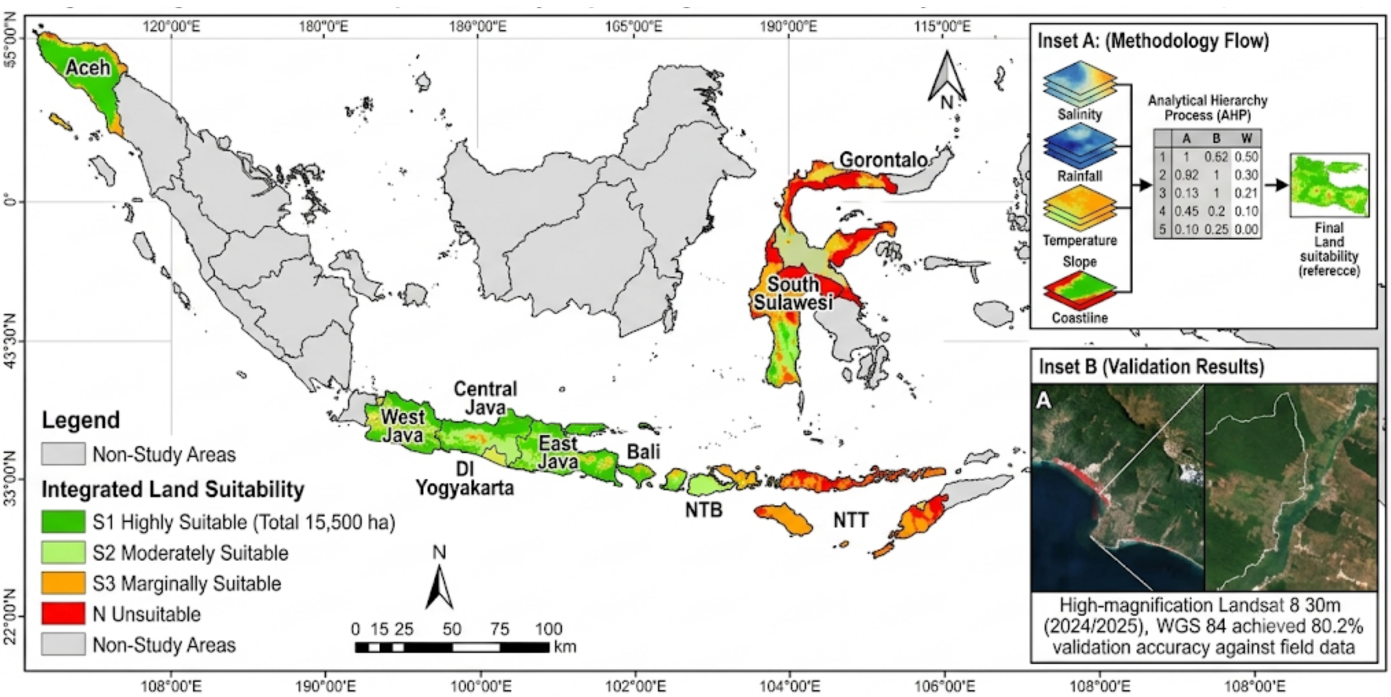

Figure 2. Geospatial analysis of land suitability for coastal salt clusters (n = 10 provinces)

3.3 Quantified productivity gains (controlled analysis)

The climate-controlled analysis isolates the performance differences between conventional systems and modernized evaporation setups. The controlled evaluation confirms that transitioning from traditional clay beds to geomembrane technology delivers a statistically significant increase in seasonal output.

The empirical mean productivity for geomembrane-lined ponds reaches 105.3 tons/ha/season, contrasting with the 65.8 tons/ha/season recorded for traditional clay-bed setups. The isolated mean productivity gain stands at 39.5 tons/ha/season. The large effect size (Cohen's d = 2.18) combined with a narrow 95% CI validates that this productivity increase is driven by the technological upgrade rather than environmental background noise. The following is a Comparison of Productivity Between Traditional and Geomembrane Systems, presented in Table 3.

Table 3. Comparison of productivity between traditional and geomembrane systems

Technology Group	Sample Size (n)	Mean Productivity (Tons/ha/Season)	Standard Deviation	t-Value	df	p-Value	95% Confidence Interval (CI)	Effect Size (Cohen's d)
Traditional	165	65.8	15.2	-12.543	273	< 0.001	33.4 to 45.6	2.18
Geomembrane	110	105.3	20.5					

3.4 Socio-economic drivers of technology adoption

The binary logistic regression model screens the socio-institutional factors that influence whether a farmer adopts geomembrane technology. Multicollinearity diagnostics show acceptable stability, with all VIF resting below 2.5. The Hosmer-Lemeshow test yields a p-value greater than 0.05, verifying a reliable predictive model fit that explains approximately 42% of the adoption variance (Nagelkerke $R^2 = 0.42$) with an overall classification accuracy of 78.5%. The following are Binary Logistic Regression Results for Geomembrane Technology Adoption, presented in Table 4.

Cooperative membership emerges as the most powerful statistical determinant of technology uptake. Farmers holding active cooperative memberships are more than four times as likely to adopt geomembrane modernizations compared to non-members ($Odds\ Ratio = 4.482, p < 0.001$). Formal education levels at or above high school ($OR = 3.490$) and regular access to technical extension services ($OR = 2.586$) also exert strong positive influences on adoption behavior. Conversely, farmer age has a small but statistically significant negative coefficient ($B = -0.035, p = 0.019$), indicating that younger operators adapt more readily to modernization.

3.5 System dynamics simulation outcomes (horizon 2025–2035)

Integrating the 15,500 hectares of $S1$ spatial boundaries as physical constraints and the regression-derived kelembagaan multipliers into the Vensim SDs model generates long-term macroeconomic projections across a uniform 2025-2035 horizon that was presented in Figure 3.

The simulation shows that combining spatial cluster expansion with target institutional support accelerates technology adoption velocities across the ten provinces. Driven by the 60% average yield improvement verified in the controlled trials, aggregate national solar salt production volumes follow a steady upward trajectory. Under this unified implementation policy, the model projects a consistent increase in smallholder net household income ranging from 60% to 75% by the target year 2035 compared to the business-as-usual baseline. This growth is maintained by quality improvements that allow raw yields to qualify for higher-paying consumption and food industry processing markets.

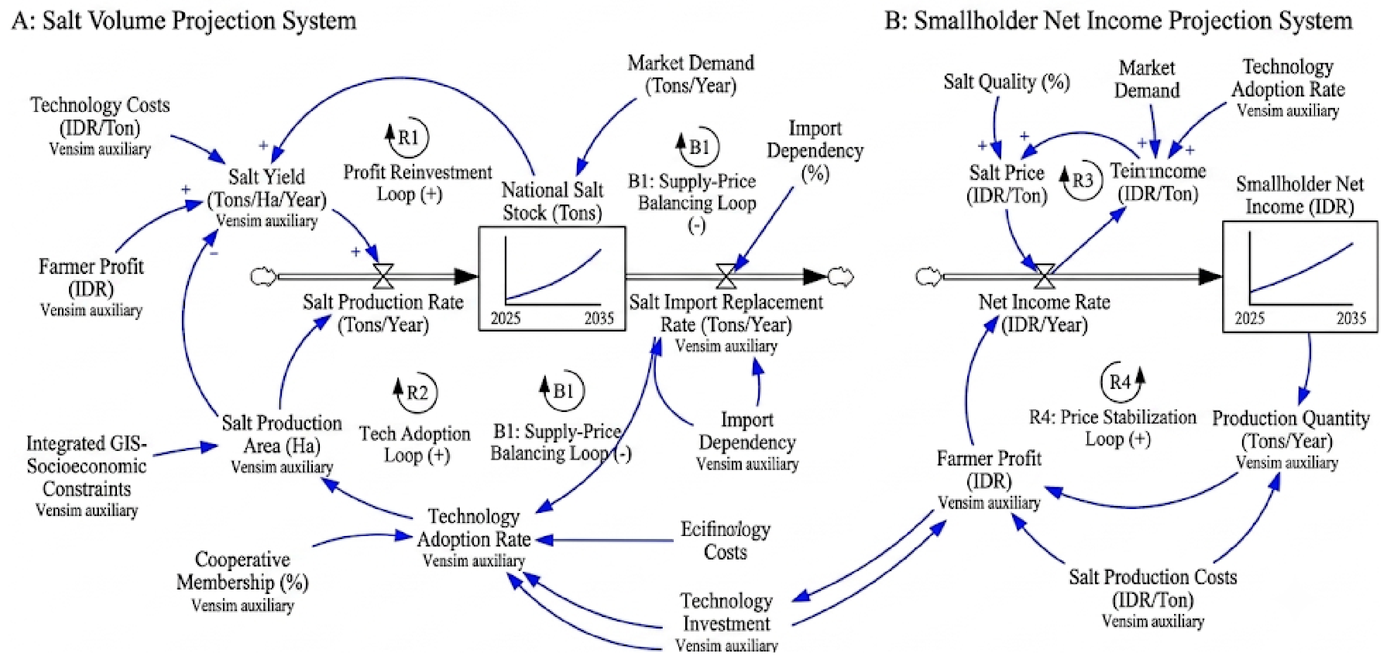

Figure 3. System dynamics (SDs) stock and flow simulation pathways for national salt volume projections (2025-2035)

Table 4. Binary logistic regression results for geomembrane technology adoption

Independent Predictor Variables	Coefficient (*B*)	Standard Error (*SE*)	Wald	df	Significance (*p*)	Odds Ratio (*Exp(B)*)
Cooperative Membership (Yes)	1.500	0.400	14.06	1	< 0.001	4.482
Education Level (≥ High School)	1.250	0.450	7.72	1	0.005	3.490
Access to Counseling (Yes)	0.950	0.350	7.37	1	0.007	2.586
Land Area Size (Hectares)	0.850	0.300	8.03	1	0.004	2.340
Age of Farmer (Years)	-0.035	0.015	5.48	1	0.019	0.966
Constant	-2.500	0.800	9.77	1	0.002	0.082

4. DISCUSSION

4.1 The SEGAR conceptual model strategy

The empirical findings from this study validate the design of the Integrated and Sustainable Community Salt Business Area (SEGAR Cluster Model). Identifying 15,500 hectares of highly suitable ($S1$) land provides a concrete geographical foundation that prevents the fragmented, uncoordinated land-use practices common in previous development schemes. By targeting volume-based clusters in areas like East Java and East Nusa Tenggara, and value-based clusters in land-constrained areas like Aceh and Yogyakarta, the framework aligns physical land capability with regional market dynamics. The SDs simulation demonstrates that this structured clustering approach yields a consistent 60% to 75% increase in net farmer income by the 2035 horizon, proving that linking spatial data directly to socio-institutional scaling mechanisms outperforms isolated technological or financial interventions.

4.2 Technical and environmental mechanisms of smart salt farming

The significant productivity leap from 65.8 to 105.3 tons/ha/season demonstrated in our results is fundamentally driven by specific biophysical and thermodynamic changes engineered by geomembrane linings. Traditional clay beds suffer from high thermal dissipation into the underlying soil substrate, slowing down evaporation rates. In contrast, geomembrane linings maximize solar radiation absorption and trap heat within the brine layer, maintaining significantly higher water temperatures and accelerating salt crystallization rates [3, 20, 21].

From an environmental standpoint, the geomembrane serves as an impermeable barrier that blocks direct contact between the processing seawater and the ground soil. This configuration isolates the crystallization process from soil-borne heavy metals and pollutants, yielding high-purity salt that meets the standard of ≥95% NaCl required for food and industrial substitution. Concurrently, this barrier function prevents localized soil salinization and mitigates subsurface leakage risks in zones characterized by high groundwater vulnerability [20, 22, 23].

Crucially, modernizing salt fields with geomembranes shifts production towards a sustainable, zero-waste operation. Traditional farms often discard bittern as a waste stream, causing localized marine toxicity. The smooth, non-porous surface of geomembrane systems simplifies the collection, concentration, and systematic reuse of bittern within a closed loop, aligning directly with zero-liquid-discharge (ZLD) principles [24, 25]. This method allows for the recovery of valuable chemical byproducts, such as magnesium and potassium salts, minimizing the industrial footprint of smallholder operations while diversifying secondary revenue streams [25, 26].

4.3 Cross-national cluster evaluation

To contextualize Indonesia's salt sector transformation, Table 5 compares the governance and scale efficiencies of the proposed SEGAR model against dominant international salt industry architectures. Linkages within smallholder-driven cooperative networks, such as those found in Gujarat, India, highlight the power of decentralized clustering to foster collective efficiency and flexible market specialization among small enterprises [27, 28]. However, as observed in both Indian and Indonesian traditional sectors, smallholder-only clusters frequently face severe scale-efficiency ceilings due to restricted technical capital, fragmented landholdings, and weak financial backing [29, 30].

Conversely, large-scale corporate clusters in Shandong, China, and Western Australia optimize scale efficiency and global cost-competitiveness through heavy research and development investments, advanced automation, and deep vertical integration [31]. Yet, these highly centralized corporate models carry high social costs, frequently creating monopolistic landscapes that displace traditional artisanal producers and reduce local community inclusivity [32]. The following is the Cross-National Cluster Evaluation, presented in Table 5.

Table 5. Cross-national cluster evaluation

Country/Cluster Model	Governance Structure	Scale Efficiency	Social Inclusivity & Market Target	Ref.
Indonesia *(Proposed SEGAR Model)*	Inclusive, decentralized smallholder cooperatives driven by targeted state multi-stakeholder interventions.	High potential efficiency; optimizes output by binding spatial GIS constraints to dynamic technology adoption parameters.	High community inclusivity; prioritizes smallholder equity and domestic industrial import replacement.	[29]
India *(Gujarat Cluster)*	Decentralized, community-driven cooperative networks relying on flexible specialization and asset pooling.	Moderate efficiency; limited by individual capital caps and highly dependent on external technical and state financial support.	High inclusivity; preserves traditional livelihoods while targeting domestic consumption and regional markets.	[28, 30]
Australia	Corporate-led, highly	Maximum efficiency; powered by	Low inclusivity; relies entirely on	[33]

(Western Australia)	centralized private ownership focusing on internal company logistics.	heavy automated infrastructure, large solar saltfields, and intensive R&D investments.	industrial-scale corporate setups, risking the displacement of artisanal producers; highly export-oriented.	
China *(Shandong Cluster)*	Centralized, vertically integrated alliances combining state-owned enterprises and large private corporations.	High efficiency; optimized through large industrial scales, lean processing systems, and tight upstream-downstream coupling.	Low-to-moderate inclusivity; prioritizes centralized growth targets, carrying high risks of monopolization and local artisanal mining exclusion.	[34]

The proposed framework resolves this trade-off. By integrating high-Technology Readiness Level (TRL) geomembrane modernizations into an inclusive cooperative governance framework, the SEGAR model achieves the technological precision and quality standards of corporate systems without sacrificing smallholder land ownership or coastal social equity.

4.4 Policy roadmap and national flagship research agenda

Our binary logistic regression model identified cooperative membership as the strongest predictor of technology uptake ($Odds\ Ratio = 4.482$), proving that technology transfer cannot rely on linear, individualistic dissemination models. Implementing the multi-year Nusantara Sea Salt Blueprint (NSSB) requires moving away from conventional top-down policies that exclude community perspectives, which historically cause marginalization, resistance, and conflicts within marine spatial planning frameworks [35-37]. Sectoral policy fragmentation between fisheries management, industrial trade regulations, and agrarian land reforms routinely undermines long-term developmental blueprints [38, 39].

To counter these structural bottlenecks, the proposed fishbone research roadmap operates as a polycentric, non-linear innovation system. By embedding academic research centers, the National Research Agency (BRIN), and smallholder cooperatives into an interconnected multi-stakeholder network, the framework bridges central governance institutions and local coastal actors [40, 41]. Cooperative networks serve as institutional hubs that handle data verification, pool capital to mitigate economic stressors, and deliver continuous technical training, resolving the education and awareness deficits that typically halt technology transfer in developing maritime economies [42-44].

The following is the Proposing Nusantara Sea Salt Blueprint (NSSB) Research Flagship Fishbone for Indonesian Salt Independence, presented in Figure 4.

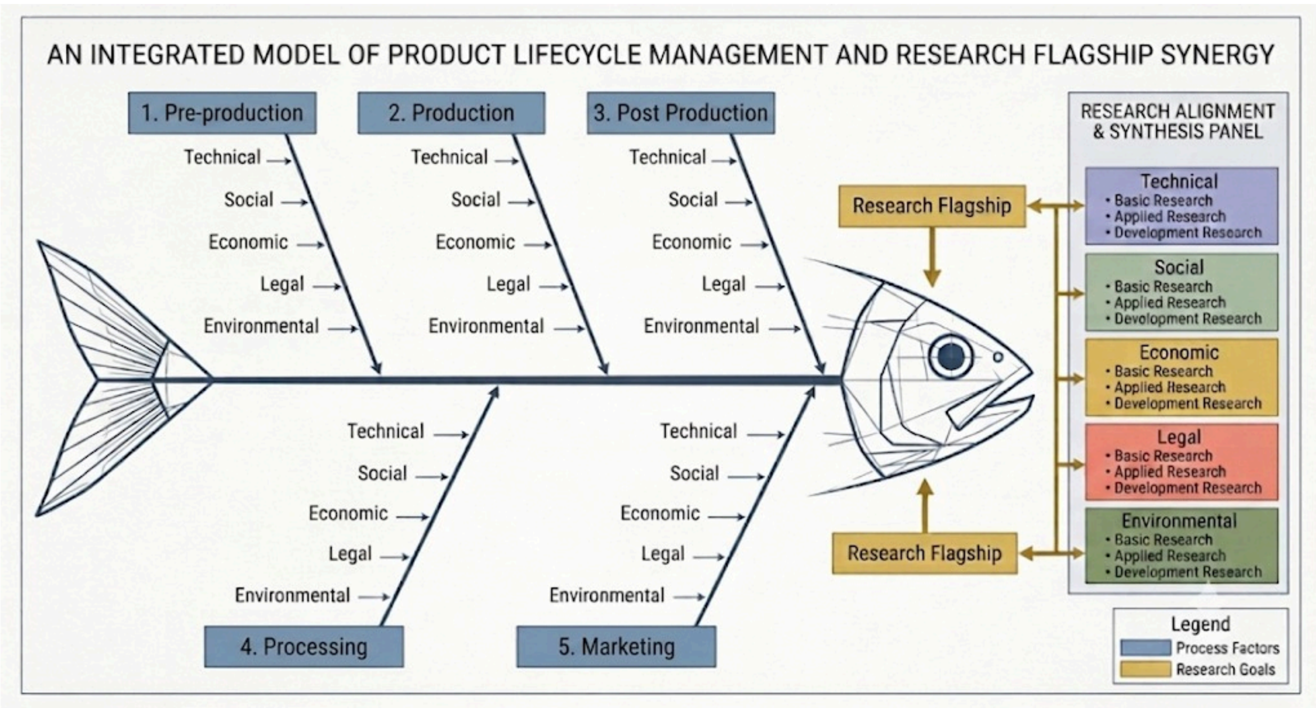

Figure 4. Proposing Nusantara Sea Salt Blueprint (NSSB) Research Flagship Fishbone for Indonesian Salt Independence

4.5 Framework limitations and future paths

Despite its robust integration, several boundaries limit the immediate generalizability of this framework. First, while geomembrane technology significantly elevates salt yields and purities, long-term material exposure to solar UV radiation and hypersaline friction introduces risks of polymer degradation and subsequent microplastic contamination in the harvested salt [22, 45]. Future flagship research must prioritize the material science engineering of bio-based or highly durable solar evaporators to eliminate microplastic shedding risks [26].

Second, the high initial capital investment required for geomembrane installation and cluster infrastructure remains a steep entry barrier for independent, small-scale operators living under acute socioeconomic stressors [21, 46, 47]. Consequently, the success of the SDs projection remains highly dependent on sustained government financial subsidies and targeted credit incentives through institutional banking channels.

Finally, our cross-sectional research design captures socio-demographic and environmental conditions within a single time bracket. Future research directions should deploy longitudinal tracking and agent-based modeling to better map shifting socio-cultural traditions, community trust dynamics, and the evolving impacts of macro-stressors like sea-level rise and saltwater intrusion on smallholder behavioral adaptation.

5. CONCLUSION

This study successfully developed and evaluated an integrated GIS-socioeconomic framework that delivers a clear, data-driven pathway toward national salt self-sufficiency. Addressing the primary research objectives, the geospatial framework processed 2024/2025 biophysical data to identify a total aggregate area of 15,500 hectares of Highly Suitable ($S1$) land across ten provinces, establishing a precise boundary condition for structured cluster expansion. Within these production zones, the climate-controlled evaluation isolated a substantial quantitative advantage for technological modernization, proving that transitioning from traditional clay beds to geomembrane systems drives a statistically significant productivity leap from 65.8 to 105.3 tons/ha/season.

However, the inferential behavioral analysis demonstrates that technical efficiency gains are structurally bounded by socio-institutional readiness. Active cooperative membership emerged as the most critical determinant of technology uptake, increasing adoption likelihood more than fourfold with an OR of 4.482. Consequently, targeted institutional strengthening serves as a vital prerequisite to trigger technological leapfrogging, enabling traditionally structured, fragmented smallholder networks to pool resource capital, overcome high upfront costs, and transition to sustainable, zero-waste production systems. Beyond the Indonesian context, this integrated spatial-socioeconomic model provides a highly scalable and replicable framework for other developing maritime economies seeking to bridge laboratory-scale innovations with large-scale industrial applications, mitigate external import vulnerabilities, and execute evidence-based coastal development policies.

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