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Integrating Renewable Energy and Smallholder Livelihoods: A Fuzzy-AHP Approach to Agrivoltaic Site Selection in Semi-Arid Indonesia

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ABSTRACT

The expansion of utility-scale solar energy in the Global South increasingly threatens rural livelihoods dependent on livestock grazing, yet existing spatial planning methodologies prioritize technical efficiency over social equity. This study presents a socio-ecological suitability framework that integrates livestock household density as a primary site-selection criterion, operationalized through a Fuzzy Analytical Hierarchy Process (Fuzzy-AHP) and GIS-based multi-criteria analysis applied to Nusa Tenggara Timur (NTT), Indonesia. Ten biophysical and socio-economic criteria are synthesized through Fuzzy-AHP (Consistency Ratio CR = 0.08), with results validated against national land cover data (overall accuracy: 87.19%, Kappa: 0.8434). The framework identifies substantial areas suitable for solar-livestock co-location under both community-scale and utility-scale deployment scenarios. The central contribution of this study is a planning-oriented framework that explicitly foregrounds pastoral livelihood equity in agrivoltaic site selection, demonstrating that social capacity indicators can function as a necessary precondition for just energy transition outcomes in semi-arid tropical drylands. The resulting maps constitute regional screening tools intended to support provincial spatial planning and are not engineering-grade site selection products.

Keywords

Agrivoltaics;
Energy-livestock nexus;
GIS-MCDA;
SDGs;
Tropical drylands

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1. Introduction

The accelerating global transition toward renewable energy is fundamental to achieving the United Nations Sustainable Development Goal (SDG) 7. However, the deployment of utility-scale solar photovoltaic (PV) systems requires vast land resources, which increasingly places energy targets in direct competition with agricultural production and food security. This tension is particularly acute in the Global South, where land is not merely a physical asset for energy generation but the primary source of livelihood for rural communities [1].

Agrivoltaics, the co-location of solar energy generation and agricultural activities, has emerged as a strategic solution to resolve this land-use conflict. By allowing dual land use, agrivoltaics offers a pathway to synergize energy production with agricultural resilience, potentially supporting SDG 2 (Zero Hunger) and SDG 13 (Climate Action) simultaneously [2, 3].

Despite the conceptual promise of agrivoltaics, the methodologies used to identify suitable sites remain predominantly technical. The existing literature on site selection relies on Multi-Criteria Decision Analysis (MCDA) [4, 5]. A review of recent studies indicates that these spatial models primarily prioritize biophysical variables such as solar irradiance, slope, and proximity to transmission infrastructure [6, 7, 8]. This pattern is

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List of Abbreviations

AHP	*Analytic Hierarchy Process*
ATR/BPN	*Ministry of Agrarian Affairs and Spatial Planning (Kementerian Agraria dan Tata Ruang/Badan Pertanahan Nasional)*
BIG	*Geospatial Information Agency (Badan Informasi Geospasial)*
BNPB	*National Board for Disaster Management (Badan Nasional Penanggulangan Bencana)*
BPS	*Statistics Indonesia (Badan Pusat Statistik)*
CR	*Consistency Ratio*
DEMNAS	*National Digital Elevation Model (Digital Elevation Model Nasional)*
ENSO	*El Niño-Southern Oscillation*
GIS	*Geographic Information System*
MCDA	*Multi-Criteria Decision Analysis*
NTT	*Nusa Tenggara Timur*
OAT	*One-At-a-Time (sensitivity analysis)*
OWA	*Ordered Weighted Averaging*
PLN	*State Electricity Company (Perusahaan Listrik Negara)*
PV	*Photovoltaic*
RDTR	*District Land-Use Detail Plan (Rencana Detail Tata Ruang)*
RTRW	*Regional Spatial Plan (Rencana Tata Ruang Wilayah)*
RUED	*Regional Energy General Plan (Rencana Umum Energi Daerah)*
SDG	*Sustainable Development Goal*
SI	*Suitability Index*
TFN	*Triangular Fuzzy Number*
USDA	*United States Department of Agriculture*
WLC	*Weighted Linear Combination*

consistent across diverse geographic contexts; for instance, Nassif et al. [9] applied GIS-AHP at a national scale in Iraq, weighting solar irradiance at 39.8% and slope at 18.9%, with no socio-economic livelihood indicator included.

A notable exception is Pérez Gelves and Díaz Florez [10], who incorporated social sub-criteria such as energy poverty and electricity access into an AHP framework for rural solar siting in Colombia; however, their approach assessed administrative regions rather than spatially continuous land units, and did not include any measure of livestock-based livelihood dependency or pastoral land use. For example, studies in Saudi Arabia [6], Serbia [7], and Belgium [8] prioritized physical or agronomic variables exclusively, omitting any measure of rural livelihood dependence or household vulnerability.

As Table S6 (Supplementary Materials) confirms, none of the six analogous recent studies include livestock household participation as a spatial equity criterion, despite its relevance in pastoral regions of the Global South. This exclusion of social criteria can lead to "energy injustice," where renewable energy projects inadvertently displace vulnerable populations or disrupt local livestock systems [11].

Prior GIS-MCDA studies in this domain can be broadly organized into four categories. Technical siting models identify locations based on biophysical and infrastructural criteria (e.g., solar irradiance, slope, grid proximity) with the goal of maximizing energy yield, as exemplified by Al Garni and Awasthi [6] and Doljak and Stanojević [7]. Environmental exclusion models additionally apply ecological and hazard constraints to avoid sensitive areas, a common refinement in European agrivoltaic analyses [8].

Socio-economic planning models extend the framework to incorporate proxies of community vulnerability or energy access, as demonstrated by Pérez Gelves and Díaz Florez [10] for rural Colombia, though typically at administrative-region rather than pixel scale. Agrivoltaic co-use models specifically address the dual-functionality of solar panels and agricultural production on the same land, such as Dupraz et al. [3] and Barron-Gafford et al. [2]; however, most remain agronomic in focus and do not spatially integrate pastoral livelihood dependency.

The present study bridges the third and fourth categories by constructing a spatially continuous, household-scale equity criterion—livestock participation—within an agrivoltaic co-use suitability model. This research addresses this academic gap by developing a socio-ecological spatial framework that integrates livestock household density as a core criterion for site suitability. The framework proposed here advances beyond previous GIS-MCDA studies in two specific respects.

First, livestock-related criteria carry a combined operational weight of 25.0% in the final suitability index, the single most influential composite dimension, with solar radiation contributing 18.5%. Second, the framework operationalizes the distinction between density and participation as separate spatial indicators, targeting the most socio-economically dependent communities, not merely the most livestock-dense areas, a distinction with direct implications for energy justice outcomes.

Indonesia possesses substantial renewable energy potential, with solar photovoltaic ranked as a top priority for sustainable electricity generation [12]. We validate this framework through a case study in Nusa Tenggara Timur (NTT), Indonesia, a prototypical tropical dryland characterized by high solar irradiance yet severe climatic vulnerability and high economic dependence on livestock. By applying a Fuzzy Analytical Hierarchy Process (Fuzzy-AHP) to synthesize physical, climatic, and socio-economic variables, this study demonstrates how GIS-MCDA can be evolved from a technical mapping tool into a mechanism for equitable sustainable development planning.

2. Materials and Methods

The methodology integrates multi-source geospatial data processing with multi-criteria decision analysis across four sequential phases: (1) framework conceptualization, (2) data acquisition and standardization, (3) Fuzzy-AHP weighting, and (4) spatial overlay and scenario generation.

2.1 The Socio-Ecological Suitability Framework

This study aims to transcend traditional techno-economic assessments by developing a spatial decision-support framework that explicitly integrates social equity into renewable energy planning. The framework conceptualizes agrivoltaic suitability as the intersection of three analytical dimensions:

1. Biophysical Feasibility: This dimension evaluates the fundamental capacity of the land to support both photovoltaic infrastructure and forage production. It aggregates climatic variables (solar radiation, temperature, rainfall) and physical terrain characteristics (slope, elevation, soil texture).
2. Socio-Economic Compatibility: This dimension operationalizes the concept of "energy justice" by treating livestock-based livelihoods as a primary siting criterion. Rather than viewing rural populations as a constraint, the framework prioritizes areas with high livestock household density and participation, thereby targeting agrivoltaic deployment to communities that would benefit most from dual-use ecosystem services.
3. Environmental and Risk Safeguards: This dimension acts as an exclusionary filter to ensure ecological integrity and infrastructure resilience. It incorporates hazard susceptibility (floods, landslides, seismic activity) and conservation buffers to prevent maladaptation.

These three dimensions interact through a sequential logic: Biophysical Feasibility generates the core suitability signal; Socio-Economic Compatibility modulates it by prioritizing areas with the greatest livelihood co-benefits; and Environmental and Risk Safeguards acts as a hard exclusion filter, removing cells within protected areas, high-hazard zones, or settlement buffers regardless of their biophysical or socio-economic score. The dimensions are structured hierarchically (Figure 1) and processed using Fuzzy-AHP to address ambiguity in balancing diverse stakeholder objectives [13].

2.2 Study Area Description

The proposed framework is empirically validated in Nusa Tenggara Timur (NTT), Indonesia (8°–12°S, 118°–125°E), a region selected as a prototypical tropical dryland. NTT covers approximately 47,350 km² and is characterized by a semi-arid climate with a distinct dry season lasting 8 to 9 months and annual rainfall ranging from 900 to 1,500 mm. Despite these climatic constraints, the province possesses exceptional solar resources, with irradiation reaching 5.7 kWh/m²/day in eastern zones.

Crucially, NTT represents a critical case for the energy-livelihood nexus because of its high economic dependence on agriculture. The province records the highest proportion of livestock-farming households in Indonesia (53.5%), making pastoralism the socio-cultural backbone of the rural economy[14]. This combination of high solar potential, climatic vulnerability, and livestock dependency renders NTT an ideal laboratory for testing equitable agrivoltaic planning models.

From a policy perspective, NTT remains among Indonesia's least electrified provinces, with grid access concentrated in major district capitals. The provincial government has identified solar PV as the primary

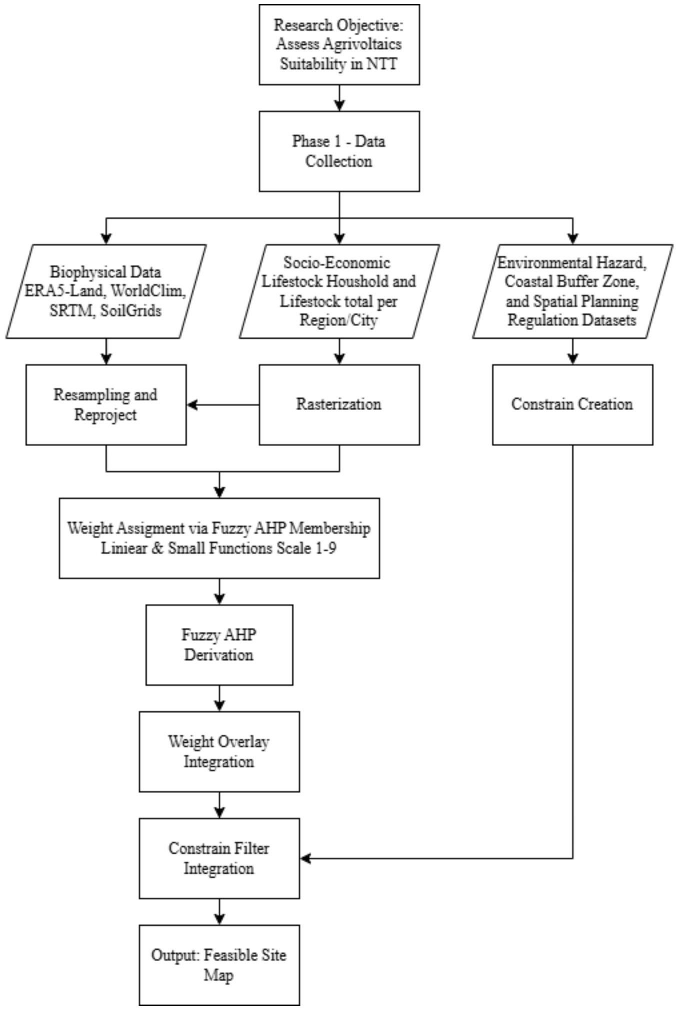

Figure 1: Conceptual Framework Diagram.

strategy for outer island electrification under the RUED NTT 2019-2050, targeting 23% renewable energy share by 2025 and 31% by 2050. Existing initiatives, including PLN's solar-diesel hybrid systems in Rote Ndao and Sumba, demonstrate institutional receptiveness to decentralized solar deployment, yet have been implemented without explicit spatial consideration of pastoral land use, reinforcing the need for the equity-sensitive framework proposed here.

2.3 Data Acquisition and Standardization

A multi-source geospatial database was constructed to populate the suitability model. All datasets were projected to WGS84 UTM Zone 51S, resampled to a standardized spatial resolution of 250 m, and clipped to the administrative boundaries of NTT Province. The input data were categorized into three domains:

1. Climatic and Physical Data: Solar radiation data were derived from ERA5-Land reanalysis (2020-2024), while rainfall and temperature datasets were obtained from WorldClim v2.1. Topographic variables (slope, elevation) were generated from the National Digital Elevation Model (DEMNAS, 8.25 m resolution), and soil texture data were sourced from SoilGrids.
2. Socio-Economic Data: Livestock household density and participation ratios were extracted from the 2023 Agricultural Census [14]. This census data is critical for the framework's novelty, allowing for the spatial identification of smallholder clusters.
3. Constraint Layers: Land cover data from the Geospatial Information Agency (BIG, 2022) were used to mask protected forests. Disaster

risk maps (flood, landslide, seismic) were obtained from the National Board for Disaster Management (BNPB, 2023).

Several preprocessing decisions were made to manage potential inconsistencies arising from differences in dataset resolution and temporal coverage. For resolution harmonization, all raster layers were resampled to a common 250 m grid using bilinear interpolation for continuous variables (solar radiation, temperature, rainfall, elevation) and nearest-neighbor resampling for categorical variables (land cover, disaster risk class) to preserve discrete class boundaries.

Regarding temporal consistency, the ERA5-Land climate data (2020-2024) and the 2023 Agricultural Census represent broadly contemporaneous conditions. The WorldClim v2.1 rainfall data (1970-2000 long-term averages) was retained because no district-level annual rainfall data at comparable spatial coverage was available for the 2020-2024 period; this introduces a known temporal mismatch acknowledged as a limitation in Section 4.5.

Following data acquisition and preprocessing, all input criteria were standardized to a common suitability scale prior to weighted aggregation. Each input criterion was standardized using continuous fuzzy membership functions, ensuring that the model operates as a genuine fuzzy inference system rather than a simple discrete reclassification. Three functional forms were applied depending on the ecological and engineering behavior of each criterion.

For monotonically increasing criteria (e.g., solar radiation), a linear increasing membership function was applied:

$$\mu(x)=\begin{cases}0 & x\le a\\ \dfrac{x-a}{b-a} & a<x\le b\\ 1 & x>b\end{cases} \tag{1}$$

For monotonically decreasing criteria (e.g., slope), a linear decreasing function was used:

$$\mu(x)=\begin{cases}1 & x\le a\\ \dfrac{b-x}{b-a} & a<x\le b\\ 0 & x>b\end{cases} \tag{2}$$

For criteria with an optimal intermediate range (e.g., rainfall, temperature, livestock density), a symmetric triangular membership function was applied:

$$\mu(x)=\begin{cases}0 & x\le a\\ \dfrac{x-a}{b-a} & a<x\le b\\ \dfrac{c-x}{c-b} & b<x\le c\\ 0 & x>c\end{cases} \tag{3}$$

where *a* and *c* are the lower and upper boundary values at which suitability is zero, and *b* is the peak optimum value at which $\mu(x)=1$. The continuous membership output $\mu(x)\in[0,1]$ was subsequently rescaled to the 1–9 suitability range via linear transformation: $S=1+8\cdot\mu(x)$. Defuzzification of the final weighted suitability surface was performed using the centroid (center of gravity) method [15]:

$$SI_{\text{crisp}}=\frac{\int x\cdot\mu_{SI}(x)\,dx}{\int \mu_{SI}(x)\,dx} \tag{4}$$

This approach ensures that the suitability model captures the continuous gradation of land quality rather than imposing abrupt categorical boundaries. The specific threshold parameters (a, b, c) for each criterion were derived from photovoltaic engineering benchmarks (solar radiation, temperature), agronomic forage productivity studies (rainfall), USDA soil engineering criteria (soil texture), and empirical pastoral intensity ranges from the 2023 Agricultural Census (livestock density). Full documentation of all threshold values is provided in Tables S2a to S2f of the Supplementary Materials.

2.4 Fuzzy-AHP Weighting Strategy

To determine the relative importance of each criterion, this study employed the Fuzzy Analytic Hierarchy Process (Fuzzy-AHP) [16]. Classical AHP is often criticized for its inability to handle the imprecision of human judgment; therefore, Fuzzy-AHP was utilized to convert linguistic variables into Triangular Fuzzy Numbers (TFNs).

The Fuzzy-AHP weighting procedure was conducted across a two-level hierarchical structure. These two levels operate at different tiers of the decision architecture.

At Level 1 (Main Criteria), five composite factors were subjected to expert pairwise comparison: (1) Energy Potential [Solar Radiation], (2) Livestock Socio-Economic Capacity, (3) Soil Suitability, (4) Thermo-Humidity Conditions [Temperature], and (5) Rainfall. The pairwise comparisons at this level (Table S3b) yielded the principal weights: Solar Radiation (25.8%), Livestock Capacity (19.7%), Soil (18.8%), Temperature (17.9%), and Rainfall (17.8%), with a Consistency Ratio of CR = 0.08, confirming acceptable consistency [15].

At Level 2 (Sub-Criteria), the ten individual input layers (Table S3a) were mapped onto their respective Level 1 parent factors. Solar Radiation ($w_i = 0.185$) corresponds to the Energy Potential factor. The Livestock Capacity factor is populated by two sub-indicators: Livestock Density ($w_i = 0.160$) and Livestock Household Participation Ratio ($w_i = 0.090$), yielding a combined livestock contribution of 0.250 to the suitability index.

Rainfall (0.120) and Temperature (0.090) form the climatic sub-criteria; Slope (0.100), Elevation (0.070), and Soil Texture (0.060) populate the terrain and soil domains; while Land Cover (0.055) and Disaster Risk (0.070) function as Boolean constraint modifiers applied as exclusion filters at the final spatial integration step. The complete two-level hierarchical structure is illustrated in Figure 2.

The Livestock Socio-Economic Capacity criterion was operationalized through two sub-indicators: Livestock Density ($w_i = 0.160$) and Livestock Household Participation Ratio ($w_i = 0.090$). Livestock Density carries the higher individual weight because it functions as a spatially continuous indicator of pastoral land-use intensity, directly interpolable at 250 m resolution from the 2023 Agricultural Census. Livestock Household Participation Ratio serves as an equity-correcting modifier that targets communities where livelihoods are structurally dependent on grazing.

A household participation majority of 50% or above implies structural economic dependence on pastoral systems, whereas raw livestock density can be inflated by a small number of commercial ranchers. This rationale aligns with energy justice principles that prioritize the most vulnerable and dependent communities [11]. In the final operational suitability index, the combined livestock contribution (0.160 + 0.090 = 0.250) exceeds that of any individual sub-criterion, including the Solar Radiation sub-criterion ($w_i = 0.185$).

The Level 1 pairwise comparisons were determined through structured literature synthesis and author expert judgment, consistent with AHP applications in energy planning under data-scarce conditions [13], following precedents in developing country contexts [10]. The

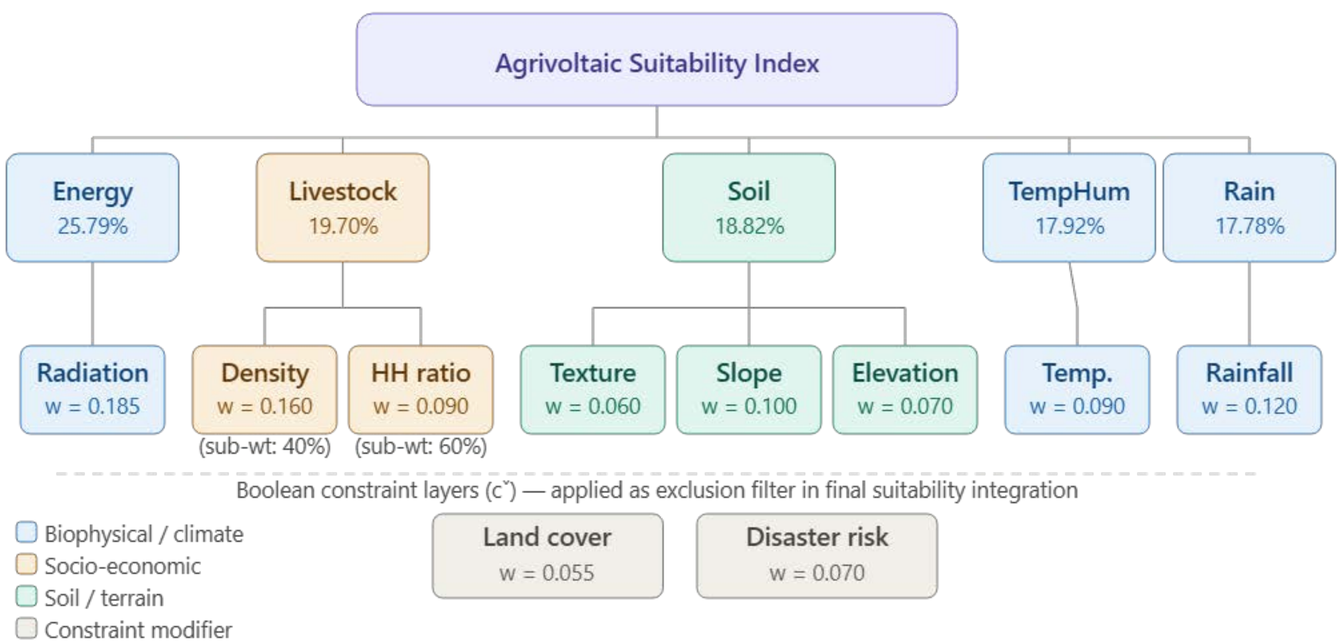

Figure 2: Two-level Fuzzy-AHP hierarchical structure.

resulting weight vector was validated by the Consistency Ratio (CR = 0.08 < 0.10) [15]. Future iterations should incorporate multi-stakeholder elicitation to externally validate the weight structure.

To be explicit about the elicitation process: pairwise comparison matrices were completed by the four authors, whose disciplinary backgrounds collectively span remote sensing, geography, spatial planning, and renewable energy systems. Judgments were made individually and then reconciled through structured discussion, with any disagreements resolved by reference to the empirical and technical literature cited for each criterion. This approach is consistent with established AHP practice in energy planning research, particularly in data-scarce developing-country contexts where formal multi-stakeholder panels are logistically constrained [10, 13].

It is important to note that the resulting weight structure is deliberately normative and planning-oriented, designed to foreground pastoral livelihood co-benefits as a planning priority rather than to identify universally optimal energy sites. This normative orientation is the study's central methodological contribution. Readers should interpret the suitability maps as reflecting an explicit equity-weighted planning framework, not as outputs of a value-neutral optimization. Future work should expand elicitation to include community representatives, local government planners, and PLN technical staff to externally validate and refine the weight structure.

To assess the robustness of the suitability results to the livestock sub-indicator weighting, a post-hoc sensitivity analysis was conducted by substituting three alternative internal weighting scenarios: 50/50, 70/30, and 40/60 (density/participation). Spearman rank correlations between the baseline suitability map and each alternative were computed across all 250 m raster cells classified as Highly Suitable, yielding values of $\rho = 0.94$ (50/50), $\rho = 0.91$ (70/30), and $\rho = 0.93$ (40/60).

The total area classified as Highly Suitable varied by less than 6% across all scenarios (range: 283,000 to 319,000 ha). The geographic core of suitability, concentrated in Kupang, Rote Ndao, and Sumba Timur, was consistently identified regardless of scenario.

A complementary one-at-a-time (OAT) sensitivity analysis was conducted by independently varying each Level 1 criterion weight by 5 percentage points while redistributing the adjustment proportionally across the remaining criteria. The Highly Suitable area changed by a maximum of 9% across all perturbations, with Livestock Capacity showing the highest influence (an area change of 8.7%) and Rainfall the lowest (3.2%). The geographic core of suitability was consistently identified across all scenarios, confirming that the framework's policy conclusions are not contingent on precise weight values, provided the general ordering of priorities is maintained.

2.5 Spatial Multi-Criteria Integration and Constraints

The final suitability index *SI* for each raster cell was calculated using the weighted linear combination method:

$$SI = \sum_{i=1}^{n} w_i \times x_i \times \prod_{j=1}^{m} c_j \tag{5}$$

Where w_i is the normalized weight of criterion i, x_i is the standardized score of criterion i, and c_j represents the Boolean constraint layers (0 = constrained, 1 = suitable).

The weighted linear combination (WLC) approach assumes full compensability among criteria: a high score on one variable can arithmetically offset a low score on another. While this is computationally tractable and widely used in GIS-MCDA studies [4, 8], it may not capture interactions between variables that are physically nonlinear. For example, the combined effect of high temperature and low rainfall on forage productivity is likely to be multiplicative rather than additive.

These nonlinear interactions represent a known limitation of the WLC approach and constitute a methodological direction for future refinement, potentially using ordered weighted averaging (OWA) or fuzzy rule-based integration. Prior to aggregation, strict exclusion criteria were applied as environmental and safety safeguards:

1. Protected Areas: All forest categories (conservation, protection, and production forests) to prevent deforestation.
2. High-Risk Zones: Areas with high susceptibility to floods, landslides, and seismic activity.
3. Settlements and Water Bodies: Built-up areas and lakes/rivers to avoid displacement and ecosystem disruption.
4. Coastal Buffers: A 500-meter buffer zone from the coastline to protect littoral ecosystems.

Only areas classified as "Open Land" (grasslands, shrublands, savannas) that passed all constraint filters were retained for the suitability analysis.

2.6 Geometric Classification and Scenario Generation

To translate the raster-based suitability results into actionable planning units, a vector-based geometric classification was performed. Suitable pixels were aggregated into polygons, simplified using the Douglas-Peucker algorithm, and filtered based on geometric compactness. Two distinct deployment scenarios were developed to evaluate policy options:

- Scenario A (Distributed Community-Scale): This scenario identifies clusters ≥3 hectares. It represents a decentralized model targeting community-owned mini-grids or cooperative-based agrivoltaic systems, aligned with rural electrification and poverty reduction goals.
- Scenario B (Centralized Utility-Scale): This scenario filters for large contiguous clusters ≥25 hectares. It represents a model suitable for industrial-scale power generation connected to the main grid, prioritizing maximum energy yield and economies of scale.

2.7 Model Validation

Validation was conducted using a stratified random sampling strategy. Reference points were allocated proportionally across all land cover classes present in the BIG 2022 national land cover map, with sample size per class determined by the relative area proportion of each class within NTT Province, subject to a minimum of 10 points per class to ensure statistical representativeness of minor classes.

In total, 445 reference points were generated, distributed across eight land cover classes: Open Land (63 points), Dryland Agriculture (14), Forest (71), Plantation (15), Water Body (28), Paddy Field/Wetland (43), Mixed Cultivation (68), and Settlement (143). This stratified design prevents dominant land cover classes from disproportionately inflating overall accuracy metrics and ensures that the performance of the model for the target Open Land class is assessed with dedicated sample support.

3. Socio-Ecological Suitability Analysis Results

This section presents the socio-ecological suitability results, progressing from individual parameter evaluations to the integrated spatial models. Key biophysical and socio-economic input variables are characterized first, followed by Fuzzy-AHP weighting results and suitability map analysis under distributed versus centralized deployment scenarios.

3.1 Environmental Parameter Classifications

Rainfall, soil texture, and temperature were standardized to 9-class systems (Tables 1-3, Figures 3-5). Rainfall ranged from 1.8 to 11.9 mm/day, with optimal zones supporting pasture growth. Temperature (20.4-27.88°C) aligned with PV efficiency at 20-25°C. Six USDA soil classes were identified, with loam (score 9) optimal for panel mounting. The suitability thresholds used for each criterion were derived from three complementary sources.

For solar radiation, classification boundaries (optimal: >5.5 kWh/m²/day) reflect PV performance benchmarks indicating grid-parity generation requires a minimum of 4.5-5.0 kWh/m²/day [6, 7]. Temperature thresholds (optimal: 20-25°C) are grounded in crystalline silicon PV efficiency curves, which show maximum power output near 25°C with measurable derating above 28.5°C.

Rainfall classification (optimal: 6.0-8.5 mm/day) draws on forage grass productivity thresholds for semi-arid savanna species, where yields decline sharply below

Table 1: Rainfall suitability score classification.

Range (mm/day)	Suitability Score (1-9)	Category suitable for vegetation growth rates
0.0 – 1.0	2	Very Dry
1.0 – 2.5	3	Dry-Low
2.5 – 4.0	5	Low
4.0 – 6.0	7	Moderately Low
6.0 – 8.5	9	Optimal
8.5 – 11.0	7	High
11.0 – 14.0	5	Very High
14.0 – 18.0	3	Very Wet
18.0 – 23.0	1	Extremely Wet

Table 2: Temperature suitability score classification.

Temperature Range (°C)	Suitability Score (1-9)	Category suitable for photovoltaic efficiency and vegetation growth rates
<12	2	Very Cold
12 – 15	3	Cold
15 – 18	5	Moderately Cool
18 – 20	7	Suitable
20 – 25	9	Optimal
25 – 27	8	Very Good
27 – 28.5	6	Warm
28.5 – 30	4	Hot
>30	2	Very Hot

4 mm/day and waterlogging stress appears above 11 mm/day. Soil texture scores follow USDA soil-structure engineering criteria for ground-mounted PV foundation stability, with sandy loam and loam ranked highest. Livestock density thresholds (optimal: 50-100 head/km²) reflect district-level pastoral intensity ranges from the 2023 Agricultural Census, calibrated to identify zones of active but non-over-intensified pastoral use.

3.2 Solar Radiation Classification

Solar radiation ranged 0-22.11 MJ/m²/day (9-class intervals, Table 4, Figure 6). Eastern islands (Sumba Timur, Rote Ndao) exceeded 20 MJ/m²/day (classes 8-9), while central highlands showed 12.5-17.5 MJ/m²/day (classes 5-7). Solar radiation's highest AHP weight (25.8%) reflects its importance. Class 7-9 zones predominate across 65-70% of non-forested land, confirming exceptional solar potential exceeding Indonesian averages.

3.3 Socioeconomic Assessment of Livestock Farming Potential

Socioeconomic analysis used Agricultural Census 2023 data, combining two sub-indicators: Livestock Density (w_i = 0.160) and Livestock Household Participation Ratio (w_i = 0.090), normalized to a 1-9 suitability scale. Livestock Density carries the higher sub-indicator weight because it functions as a spatially continuous, raster-interpolable proxy of pastoral land-use intensity.

The Participation Ratio serves as an equity-correcting modifier, identifying communities where a majority of households are structurally dependent on grazing. Top-ranked regencies (Malaka, Nagekeo, Timor Tengah

Table 3: Soil texture mapped score for photovoltaic construction.

Texture	Maped Score (1-9)	Category suitable for photovoltaic construction	Parameter
Sand	3	less suitable	The soil structure is too loose, making it difficult to support the foundation.
Loamy sand	5	quite suitable	It can still be used if the foundation is reinforced.
Sandy loam	7	suitable	Generally used for light construction
Loam	9	Very suitable	Ideal: stable, good drainage
Silt loam	5	quite suitable	Fairly good but easily waterlogged
Silt	3	less suitable	High risk of flooding
Sandy clay loam	7	suitable	The balance is good enough for the foundation
Clay loam	7	suitable	Stable and can support loads
Silty clay loam	5	quite suitable	Can be used if the slope is low
Sandy clay	7	suitable	Still safe for the foundation
Silty clay	3	less suitable	Risk of flooding
Clay	3	less suitable	Stability varies depending on humidity

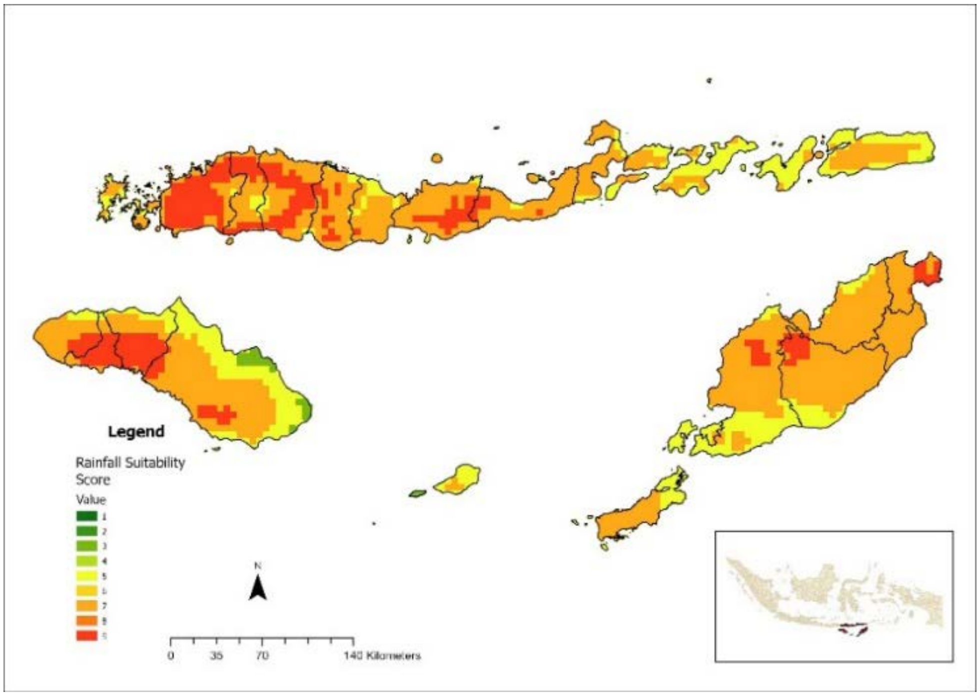

Figure 3: Rainfall (mm/day) mapped score classification.

Selatan; scores 7-8) exceeded 65% household participation (Table 5), while urban centers showed minimal potential (Table 7). The provincial average of 1.64 animals/household indicates smallholder operations with ~622,735 potential stakeholders for solar grazing partnerships (Figure 7).

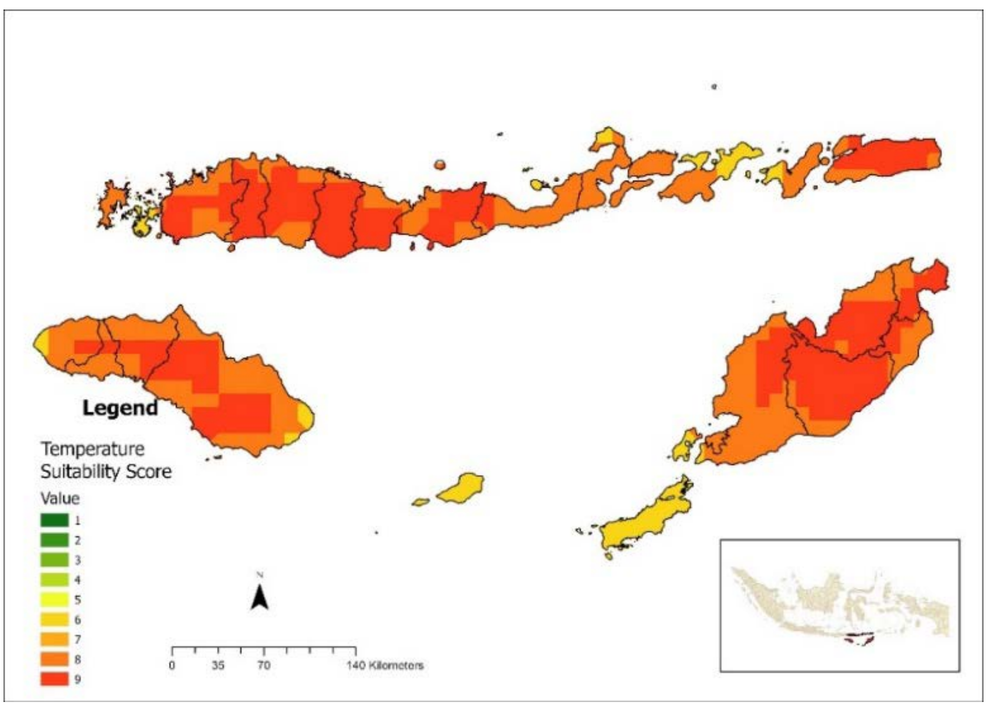

Figure 4: Temperature-mapped score classification across NTT Province.

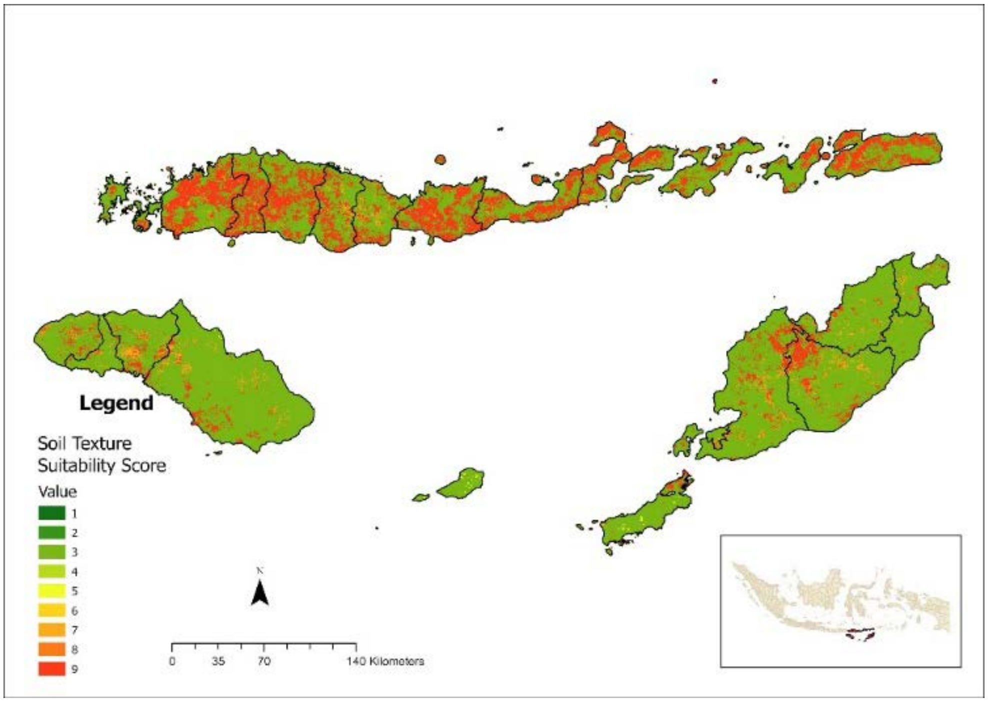

Figure 5: Soil texture mapped score classification across the province.

3.4 Multi-Criteria Integration: Weighted Overlay Results

The AHP pairwise comparison matrix and resulting weights are shown in Table 8. Figure 8 displays the final weighted overlay result showing the spatial distribution of suitability classes across NTT Province.

3.5 Constraint Integration with Weighted Overlay

Stringent exclusion criteria were applied before integrating weighted overlay scores (Figure 9). All forested areas were masked to preserve ecosystems, leaving only grasslands, shrublands, and fallow fields. A 500 m coastal buffer was imposed along shorelines. Disaster vulnerability screening removed Regency/City with moderate to high risk of floods, landslides, or seismic events. After applying masks, weighted overlay analysis was performed solely on the remaining open lands. Only areas scoring 5.0 or higher on the 1-9 scale were retained for geometric filtering.

3.6 Geometry-Based Site Selection Outcomes

Following the raster-based suitability assessment, the analysis proceeded to vector-based geometric classification to identify actionable planning units.

Table 4: Solar radiation mapped score for electrical energy potential.

Range (MJ/m²/day)	Suitability Score (1-9)	Category
0.00 – 2.50	1	Very Low
2.50 – 5.00	2	Very Low–Low
5.00 – 7.50	3	Low
7.50 – 10.00	4	Low–Moderate
10.00 – 12.50	5	Moderate
12.50 – 15.00	6	Moderate–Good
15.00 – 17.50	7	Good
17.50 – 20.00	8	Very Good
20.00 – 22.11	9	Excellent

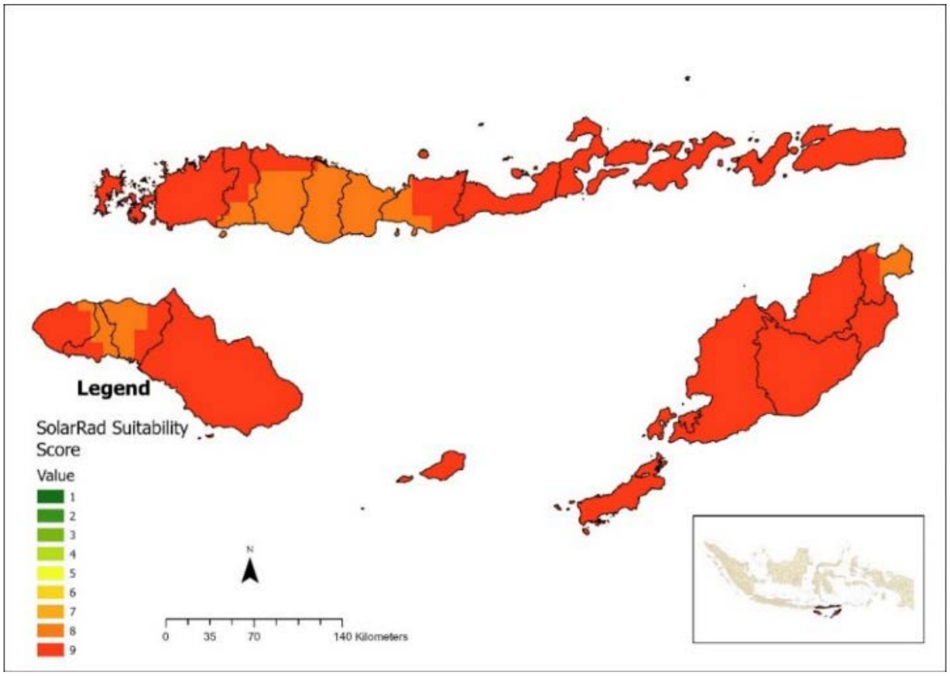

Figure 6: Solar radiation suitability score across NTT Province.

Distributed Agrivoltaics Potential (≥3 ha): Strategy A filtered 4,464 polygons meeting the ≥3 ha threshold, representing community-scale scenarios. Polygons were most numerous in western and central regencies (Kupang, Timor Tengah Selatan, Manggarai). Although large clusters occasionally occurred (>1,000 ha), predominant unit size remains 5-30 ha, suggesting decentralized installation feasibility.

Centralized Solar-Agriculture Potential (≥25 ha): Strategy B imposed a stricter ≥25 ha criterion, yielding 1,372 retained clusters concentrated in basins and low-relief alluvial plains in Kupang, Rote Ndao, Sumba Timur, and Timor Tengah Selatan. This threshold reduced the polygon count threefold while preserving approximately 31% of the total surface area.

3.7 Model Validation Results

Validation assessed accuracy by comparing delineated suitable areas against independently verified land cover data from BIG. Comprehensive accuracy assessment used 445 validation points systematically distributed across NTT Province. The confusion matrix analysis (Table S5) provides comprehensive cross-tabulation. Table 9 summarizes key accuracy metrics.

Table 5: Top-ranked socioeconomic assessment of livestock farming potential (Score 7-8).

Rank	Regency/ City	% of Total Households	Livestock Density (animals/ km²)	Socio econ Score (1-9)
1	Malaka	66.0%	53.1	8
2	Nagekeo	75.4%	38.3	8
3	Timor Tengah Selatan	70.7%	34.4	8
4	Timor Tengah Utara	66.2%	35.9	7
5	Belu	48.2%	56.9	7
6	Ngada	66.3%	25.3	7
7	Sabu Raijua	42.7%	86.8	7
8	Sumba Timur	73.7%	15.9	7
9	Kupang	62.2%	26.3	7

Table 6: Moderate socioeconomic assessment of livestock farming potential (Score 5-6).

Rank	Regency/ City	% of Total Households	Livestock Density (animals/ km²)	Socio econ Score (1-9)
10	Flores Timur	43.2%	44.9	6
11	Rote Ndao	38.1%	54.5	6
12	Alor	49.9%	37.4	6
13	Sikka	47.6%	37.9	6
14	Manggarai	61.2%	22.2	6
15	Sumba Tengah	67.3%	14.7	6
16	Manggarai Timur	60.7%	20.6	6
17	Sumba Barat Daya	60.3%	13.3	6
18	Ende	48.4%	22.6	5
19	Sumba Barat	51.4%	18.6	5
20	Lembata	40.7%	27.6	5
21	Manggarai Barat	52.9%	10.4	5

The validation yielded an overall accuracy of 87.19% (388 out of 445 points correctly classified), substantially exceeding the 85% minimum threshold commonly cited for land-use classification suitability studies [17]. The Kappa coefficient was $\kappa = 0.8434$, indicating near-perfect agreement [18]. However, a critical accuracy asymmetry must be noted for the "Open Land" category, which is the primary land-use class targeted by this framework.

Producer's Accuracy for Open Land was 79.4% (omission error: 20.6%), indicating that approximately one-fifth of actual open grazing land in the reference dataset was not captured by the model. More significantly for policy application, the User's Accuracy for Open Land was 65.8% (commission error: 34.2%), meaning that approximately one in three raster cells predicted as "suitable open land" may be misclassified as such. This commission error reflects the spectral and contextual overlap between open savanna-grassland and adjacent agricultural or mixed-cultivation land covers at 250 m resolution.

It is important to clarify that this validation concerns the internal consistency of the land-cover classification and the suitability layer's agreement with independent land-cover evidence. It does not constitute a direct validation of agrivoltaic productivity, actual project viability, or real-world energy and livelihood outcomes, which would require field-based measurement well beyond the scope of this spatial planning study.

The practical implication of this commission error is that the nominal 301,000 hectares of highly suitable land identified in this study should be interpreted as an upper-bound planning estimate. Applying a conservative correction factor based on User's Accuracy (66% confidence), the high-confidence suitable area is estimated at approximately 198,000 hectares, representing sites where the spatial model's predictions are more reliably confirmed by independent land-cover evidence. All policy-relevant analyses are therefore reported under both the nominal (301,000 ha) and high-confidence (198,000 ha) scenarios.

4. Discussion of Spatial Findings and Policy Implications

The results confirm that incorporating social equity criteria into site selection fundamentally alters the geography of suitability, shifting focus from purely high-irradiance zones to areas where energy infrastructure can coexist with pastoral livelihoods. The following sections interpret these findings in the context of sustainable development, analyzing deployment model

Table 7: Low potential socioeconomic assessment of livestock farming potential (Score 3).

Rank	Regency/ City	% of Total Households	Livestock Density (animals/km²)	Socio econ Score (1-9)
22	Kota Kupang	4.4%	35.4	3

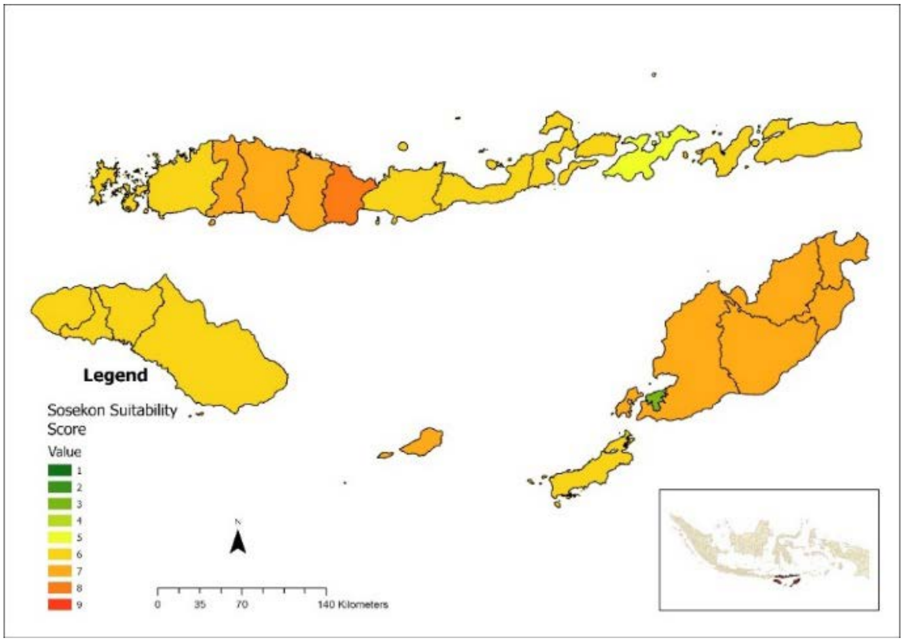

Figure 7: Socioeconomic score of livestock farming potential.

trade-offs and the potential of agrivoltaics to advance SDGs in data-scarce archipelagic regions.

4.1 Spatial Distribution and the Energy-Livestock Nexus

The spatial analysis reveals a distinct geographic pattern of agrivoltaic suitability that aligns closely with the socio-ecological structure of Nusa Tenggara Timur. The concentration of highly suitable sites in Kupang, Rote Ndao, and Sumba Timur is not merely a function of high solar irradiance (up to 5.7 kWh/m²/day) but is critically driven by the convergence of open grazing lands and high livestock household density. This overlap confirms the core premise of the Energy-Livestock Nexus: that the areas most technically viable for solar generation are often the same landscapes that sustain pastoral livelihoods.

Unlike conventional solar siting studies that prioritize remote deserts [6], our framework highlights semi-arid savannas where land competition is latent but manageable. The 301,000 hectares identified exclude forests and intensive crop fields, demonstrating that renewable energy targets can be met without compromising high-value agricultural zones or conservation areas.

4.2 Trade-offs Between Centralized and Distributed Deployment

The comparison between the distributed (Strategy A) and centralized (Strategy B) deployment scenarios highlights a fundamental policy choice for energy planners in the Global South. Strategy B, which filters for large contiguous clusters (≥25 ha), offers efficiency for utility-scale projects and simplified grid integration. However, the spatial results show that relying solely on this centralized model would exclude nearly two-thirds of the potential sites identified in the distributed model.

Strategy A (≥3 ha), by contrast, reflects a distributional logic more consistent with the socio-economic

Table 8: Pairwise comparison matrix and resulting weights.

Criterion	Weight	Percentage
Solar Radiation (Energy Output)	0.2579	25.79%
Socioeconomic (Livestock Households)	0.1970	19.70%
Soil Texture	0.1882	18.82%
Temperature & Humidity	0.1792	17.92%
Rainfall	0.1778	17.78%

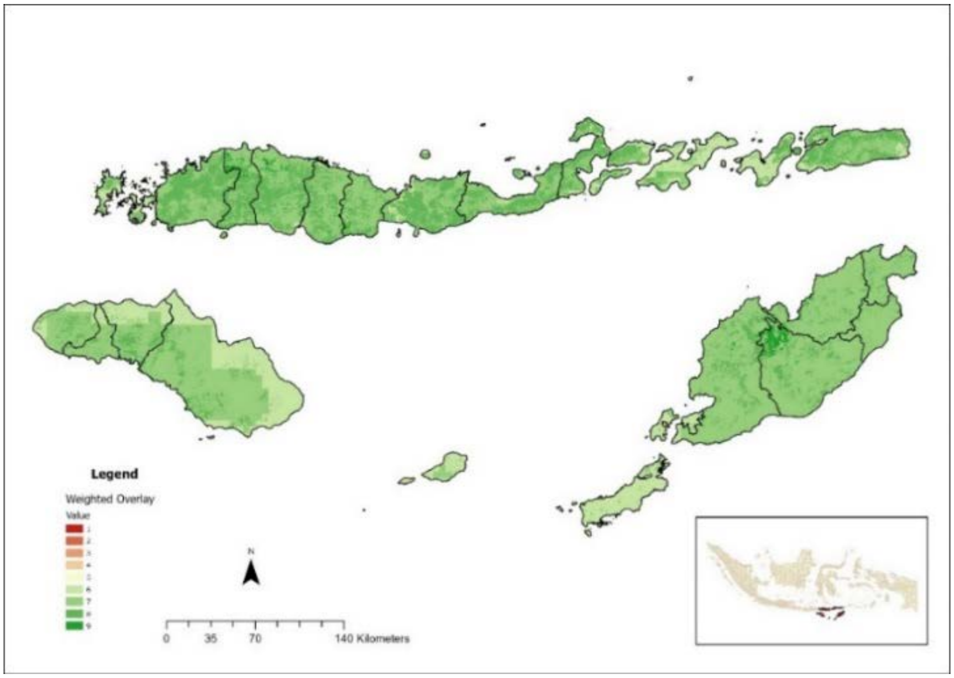

Figure 8: Final weighted overlay result showing spatial distribution.

geography of smallholder pastoral regions. Strategy A clusters are predominantly located within or adjacent to sub-districts with the highest livestock household participation rates (>50%), whereas Strategy B clusters are more frequently concentrated in lower-density pastoral zones where land consolidation is spatially feasible.

In the context of rural electrification, distributed agrivoltaic systems located near livestock clusters can function as anchor loads for microgrids, reducing transmission losses and improving grid stability in peripheral islands. This suggests that a hybrid policy approach is necessary: utilizing Strategy B sites for national grid supply while incentivizing Strategy A sites for community-based electrification and local resilience.

These strategic conclusions must be interpreted in the context of the model's classification uncertainty. Given the 34.2% commission error for the Open Land class, Strategy B sites, which require large contiguous polygons (≥25 ha), are subject to more stringent geometric filtering and are therefore more likely to correspond to genuinely open, consolidated grazing areas. Strategy A sites include smaller clusters where misclassification of individual 250 m cells has a proportionally larger effect. Consequently, Strategy B recommendations carry higher spatial confidence per unit area, while Strategy A sites require more intensive ground-truthing before investment decisions.

4.3 Implications for Sustainable Development Goals (SDGs) in Tropical Drylands

The spatial results demonstrate that agrivoltaic deployment in Nusa Tenggara Timur can simultaneously advance SDG 2 (Zero Hunger), SDG 7 (Clean Energy), SDG 1 (No Poverty), and SDG 13 (Climate Action) through a single land-use intervention. Rather than restating these linkages separately for each goal, the following subsections highlight the mechanism through which the spatial framework generates each co-benefit [2, 18, 19].

4.3.1 Contribution to SDG 2: Zero Hunger and Feed Security

In NTT's semi-arid context, the primary SDG 2 pathway operates through feed system stabilization rather than direct crop production. Because the 301,000 ha of identified suitable land overlaps directly with active open grazing territory, confirmed by the high spatial correlation between suitability scores and livestock household density, agrivoltaic co-location can reduce evapotranspiration and buffer daytime soil temperatures under panel arrays, sustaining forage biomass availability during the dry season [2, 20].

For smallholder herders in NTT, where livestock represent the primary store of household wealth and a key buffer against food insecurity, maintaining forage access

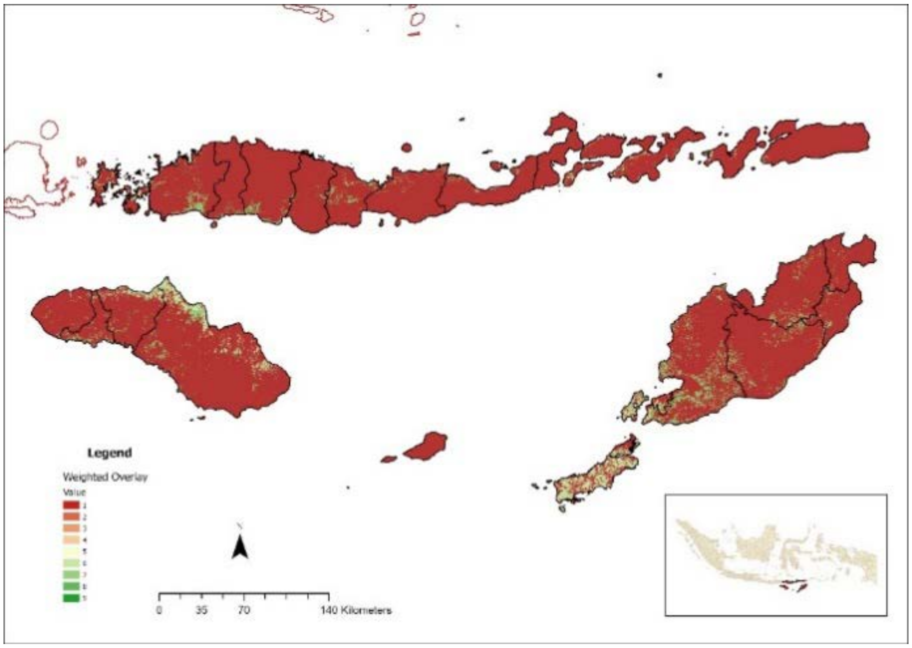

Figure 9: Constraint integration with weighted overlay.

during the 8-9 month dry season has direct implications for animal body condition, milk and meat availability, and the avoidance of distress sales. This is a spatially contingent benefit that materializes specifically in the Kupang, Rote Ndao, and Sumba Timur clusters identified by this study [18, 21].

4.3.2 Contribution to SDG 7 and SDG 1: Clean Energy and Poverty Reduction

The electricity generation potential across the 301,000 ha of identified suitable land substantially exceeds current provincial demand, confirming that dual-use land planning can accelerate SDG 7 progress in NTT without requiring greenfield land conversion. The equity implications hinge critically on deployment model.

The distributed Strategy A produces a spatial pattern that closely matches the distribution of livestock-dense rural settlements, enabling community-oriented energy models to be sited where livelihood co-benefits are highest. Evidence from Indonesia's outer island electrification programs confirms that distributed renewable systems consistently outperform centralized models in poverty reduction outcomes, particularly through enabling productive use of energy at the household and small-enterprise level [11, 22, 23, 24].

4.3.3Contribution to SDG 13: Climate Action and Dryland Resilience

NTT's exposure to ENSO-driven drought variability makes agrivoltaics' climate adaptation pathway

Table 9: Validation Accuracy Summary by Land Cover Class.

Land Cover Class	Reference Samples	Correctly Classified	Producer's Accuracy (%)
Open Land	63	50	79.4
Dry Land Agriculture	14	11	78.6
Forest	71	65	91.5
Plantation	15	13	86.7
Water body	28	23	82.1
Wetlands	43	39	90.7
Mixed Agriculture	68	50	73.5
Settlement	143	137	95.8

particularly relevant. The large renewable generation potential provides a route to displacing fossil fuel generation in a province dependent on diesel-heavy off-grid systems.

By co-locating PV infrastructure within pastoral landscapes rather than displacing them, the framework protects the land-based adaptive capacity of communities most exposed to climate variability, jointly optimizing for energy output, livelihood protection, and ecological safeguards, thereby operationalizing SDG 13's call for climate-resilient development that does not exacerbate vulnerability for marginalized groups [2, 18, 25].

4.4 Integration into Spatial Planning Processes

Translating the framework outputs into operative planning decisions requires integration with Indonesia's existing spatial governance architecture at multiple administrative levels.

At the provincial level, the suitability maps produced by this study are directly compatible with the spatial format required by Regional Spatial Plans (Rencana Tata Ruang Wilayah, RTRW), which are revised on 20-year cycles under Law No. 26/2007. Provincial planning agencies (Bappeda) could incorporate the 301,000 ha suitability layer as an overlay designation, analogous to existing kawasan peruntukan energi (energy allocation zones), within the RTRW revision cycle currently underway in NTT (RTRW 2020-2040).

At the district level, the scenario outputs (Strategy A clusters ≥3 ha; Strategy B clusters ≥25 ha) can inform the preparation of District Land-Use Detail Plans (RDTR), designating agrivoltaic-compatible subzones within open land categories. At the community level, the livestock household density layer provides a data foundation for identifying villages that should be prioritized as first movers under participatory renewable energy planning programs, such as those supported by the national Village Fund (Dana Desa) for energy infrastructure.

To operationalize these pathways, we recommend that the Ministry of Agrarian Affairs and Spatial Planning (ATR/BPN) issue technical guidance standardizing the inclusion of agrivoltaic suitability criteria within energy allocation zone delineations, particularly for provinces with high pastoral land dependence and strong solar resources.

4.5 Methodological Contributions and Replicability

Although this study focuses empirically on Nusa Tenggara Timur, the methodology is transferable to other semi-arid regions in the Global South where high solar potential coincides with livestock dependence and evolving renewable energy agendas.

Recent agrivoltaic analyses in Europe and North America emphasize technical land potentials, leaving a gap on socio-economic equity in data-poor rural contexts [19, 26]. Prior studies by Pérez Gelves and Díaz Florez [10]in Colombia and Nassif et al. [9] in Iraq took partial steps toward social integration but did not address pastoral livelihood dependency or household-level vulnerability as spatial criteria. This study bridges both gaps simultaneously.

By treating livestock household density and participation as central criteria rather than ancillary attributes, the GIS-MCDA framework developed for Nusa Tenggara Timur provides a template that can be adapted using locally available census and land-cover data elsewhere. Future applications could, for example, integrate pastoral mobility corridors in Sahelian countries, indigenous grazing rights in Andean drylands, or customary tenure systems in East African rangelands. In doing so, agrivoltaic planning can evolve from isolated pilot projects toward a systematic instrument for delivering SDG co-benefits at scale across dryland landscapes of the Global South.

4.6 Limitations and Future Directions

This section summarizes the four most critical limitations of the study that bear directly on the interpretation of results. Full technical elaboration is provided in Supplementary Note 7.

First, the ERA5-Land solar radiation dataset has a native resolution of approximately 10 km, resampled to 250 m by bilinear interpolation; this resampling does not generate new sub-10 km information. NTT's complex inter-island terrain gradients can produce terrain-induced irradiance deviations of 10-20% from ERA5-Land grid-cell averages, including shadow and aspect effects invisible at this scale (see Supplementary Note 7.1.1). The 250 m suitability map is therefore a provincial planning envelope, not a site-engineering product; on-site pyranometer measurement or DEMNAS-based ray-casting is required before any project proceeds to feasibility assessment.

Second, the 34.2% commission error for the Open Land class implies that the nominal 301,000 ha estimate has an upper-bound character; a conservative high-confidence estimate of 198,000 ha is recommended for investment planning purposes.

Third, the AHP weight structure was derived through literature synthesis and expert judgment by the authors, not through formal multi-stakeholder elicitation, which limits the weight structure's claim to representativeness.

Fourth, the socio-economic layer relies on district-level census aggregation, which cannot resolve within-district heterogeneity in grazing territory or customary land tenure arrangements (ulayat), a limitation that requires on-the-ground social mapping before project-level implementation.

Fifth, the framework does not incorporate grid connection costs, transmission access constraints, or distance to substations as explicit suitability criteria. In purely market-driven investment contexts, these factors can be decisive in determining project feasibility.

However, in the NTT context this limitation is substantially mediated by Indonesia's national policy framework for underdeveloped regions. Under Presidential Regulation No. 63/2020 and its successors, the central government is obligated to provide basic infrastructure, including electricity access, in designated underdeveloped districts. In this policy environment, grid infrastructure extension or off-grid electrification investment is a mandated government commitment rather than a purely discretionary market variable, and is typically treated as a fixed parameter in regional investment planning frameworks.

This context reinforces rather than undermines the study's emphasis on distributed agrivoltaic deployment (Strategy A): decentralized community-scale systems are precisely the modality preferred under underdeveloped electrification programs, as they reduce dependence on costly inter-island transmission extension. Nevertheless, future iterations of this framework should incorporate distance-to-substation and PLN grid coverage layers as supplementary feasibility screening criteria to support project-level decision-making.

Future research should focus on field-level validation of the microclimatic interactions between specific tropical forage species and PV shading regimes. Additionally, further work is needed to develop governance mechanisms that ensure the equitable distribution of benefits modeled in this framework, such as standardizing "solar grazing" contracts to protect smallholder rights.

5. Conclusion

This study demonstrates that integrating socio-economic equity into agrivoltaic site planning can resolve land-use competition in tropical drylands. The socio-ecological GIS-MCDA framework validated for Nusa Tenggara Timur shifts the focus from technical resource mapping toward multidimensional sustainable development planning, identifying substantial areas that are biophysically and socially suitable for dual solar-livestock use without displacing key food systems or vulnerable groups.

The comparative assessment of centralized versus distributed deployment strategies emphasizes that a distributed, community-focused model is critical for ensuring that agrivoltaic benefits reach the rural poor, especially in fragmented archipelagic regions. Furthermore, the co-location of solar panels and grazing land offers not only energy and food security co-benefits but also increased climate resilience, directly supporting SDG 2, SDG 7, and SDG 13. The proposed framework is readily adaptable to other dryland contexts in the Global South, providing a replicable planning template for policymakers confronting the food-energy-land trilemma.

While empirical validation of livelihood outcomes lies beyond the scope of this study, the spatial framework identifies sites where the structural conditions for equitable co-benefits, high pastoral dependence, strong solar potential, and community-scale feasibility, co-occur. Operationalizing the energy-livestock nexus through spatially explicit, equity-sensitive planning thus represents a necessary precondition, if not a sufficient guarantee, for just and climate-smart renewable energy transitions in semi-arid pastoral regions.

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