

*Research Article*

Geographic Information System-Adjusted Rural Access Screening Framework for Solar Photovoltaic Intervention Planning in Indonesia

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Abstract: Rural solar photovoltaic (PV) intervention planning in archipelagic countries requires more than electrification ratios because road access, inter-island logistics, construction burden, solar resource, and local intervention need shape the remaining underserved settlements. This study develops a provincial screening framework for rural PV intervention planning in Indonesia by adapting the Rural Access Index (RAI) into a Geographic Information System (GIS)-adjusted Rural Access Index (ARAI) as an implementation-difficulty layer. The method estimates ARAI and road access deficit (RAD) using a 2-km road buffer, rural population masks, national road-condition scenarios, selected OpenStreetMap regency roads, and a port-access sensitivity layer. ARAI/RAD is then combined with underdeveloped-village status, household electricity deficit, non-utility household reliance, remote-village irradiation, and the Construction Cost Index (CCI) to construct the intervention need, solar suitability, implementation difficulty, and planning typology. The results show that the mean ARAI ranges from 45.8% in the baseline scenario to 53.0% in the most inclusive scenario, confirming persistent rural road-access constraints. The rural population mask affects ARAI more than the International Roughness Index threshold or port layer. The most access-constrained screening contexts include parts of Kalimantan, Nusa Tenggara, Maluku, and Papua, while the final typology separates near-term candidates, strategic candidates requiring logistics and subsidy support, design-check provinces, solar-opportunity provinces, and monitoring groups. The typology is a robust provincial pre-feasibility tool based on weight-sensitivity and qualitative validation checks. The contribution of this study is a transferable ARAI-based framework that links rural accessibility, electricity need, solar suitability, and implementation burden before conducting feasibility studies at the village level.

Keywords: Archipelagic rural electrification; Geospatial analysis; Off-grid solar photovoltaic; Rural Access Index; Rural energy planning

1. Introduction

Rural electricity planning has moved from a simple connection-expansion problem to a final-mile infrastructure problem. Globally, the remaining electricity-access gap is increasingly concentrated in rural, remote, dispersed, island, or otherwise hard-to-reach settlements where low demand density, long supply chains, weak transport infrastructure, difficult maintenance conditions, and limited local technical capacity raise the cost and risk of conventional grid extension (Bhatia & Angelou, 2015; Energy Sector Management Assistance Program (ESMAP), 2022; Energy Sector Management Assistance Program (ESMAP) et al., 2024; International Energy Agency (IEA) et al., 2025). This makes rural electrification a spatial planning problem as much as an electrical engineering problem. A location may be technically suitable for PV generation, but it may still be a poor near-term candidate if transport access, installation logistics, public subsidy requirements, or operation and maintenance capacity are not addressed.

Therefore, recent energy-access literature treats access as multidimensional rather than binary. The Multi-Tier Framework emphasizes capacity, duration, reliability, quality, affordability, legality, health, and safety instead of merely counting household connections (Bhatia & Angelou, 2015). The off-grid and mini-grid literature similarly shows that solar home systems, PV mini-grids, and PV-battery-diesel hybrids can support rural electrification and de-dieselization. However, their performance depends on demand scale, storage requirements, institutional arrangements, tariff design, productive-use potential, and long-term maintenance (Babayomi et al., 2023; Bhattacharyya, 2012; Energy Sector Management Assistance Program (ESMAP), 2024; International Energy Agency Photovoltaic Power Systems Programme (IEA PVPS), 2014; International Renewable Energy Agency (IRENA), 2019; Mandelli et al., 2016; Zebra et al., 2021). In other words, technology choice is necessary but not sufficient; early screening must identify where the intervention is socially justified, where the solar resource is promising, and where implementation barriers are severe.

Studies on rural development and planning have reached a similar conclusion. Access is not only a matter of being geographically rural; it concerns the ability of households and communities to access services, markets, infrastructure, public facilities, and economic opportunities. Integrated rural accessibility planning explicitly links infrastructure investment with service access and local development needs (Abreu et al., 2022; Donnges, 2003; European Union et al., 2021; OECD, 2018, 2025). National remoteness systems, such as the Canadian Index of Remoteness and the Australian Statistical Geography Standard Remoteness Structure, also demonstrate that distance, network travel, population-service hierarchy, and settlement structure can be formalized as planning indicators (Australian Bureau of Statistics, 2023; Statistics Canada, 2023). These approaches are relevant to rural electricity planning because physical access networks deliver, repair, and sustain electricity infrastructure.

RAI is the most established global indicator of rural transport access. This measure measures the proportion of Rural Population (RP) living within 2 km of an all-season road and is used as a Sustainable Development Goal (SDG) indicator 9.1.1 (Roberts et al., 2006; United Nations, 2024; World Bank, 2016, 2019). Recent methodological studies have strengthened the use of gridded population data, open road networks, satellite-derived settlement information, and reproducible geospatial workflows for RAI estimation (Iablonovski et al., 2024; Sun et al., 2023; Workman & McPherson, 2021). These advances are important for data-constrained countries because they allow screening to begin before the availability of official road condition and village-level accessibility datasets. Nevertheless, RAI remains a transport indicator. It does not directly measure electricity access deficit, non-utility electricity reliance, solar resource quality, construction cost, diesel dependence, or local implementation capability.

Indonesia is a strong test case for this methodological problem. The country has achieved high aggregate electrification, but aggregate ratios can conceal remaining unelectrified households, reliance on non-PLN electricity, and Underdeveloped Villages (UDV) located in outer-island, mountainous, forested, coastal, or frontier settings (Asian Development Bank (ADB), 2016, 2020; BPS-Statistics Indonesia, 2024b; Directorate General of Electricity, 2025; Kemendesa PDTT, 2024; Pambudi et al., 2023). In archipelagic geography, remoteness is not simply the distance from the nearest grid or road. It includes inter-island access, port dependence, road continuity, construction-cost variation, fuel logistics, and the ability to service PV and battery equipment after installation. Existing policy discussions on Indonesia's remote grids identify diesel dependence, high logistics cost, and limited scalability of isolated microgrids as persistent constraints (Ali et al., 2024; Guild, 2019; Simatupang et al., 2021; Sulaeman et al., 2021).

Existing electricity-planning methods provide useful but incomplete tools for solving this problem. Geospatial least-cost electrification models, including OnSSET and related approaches, combine settlement data, demand assumptions, distance to grid, resources, and technology-cost assumptions to compare grid extension, mini-grid, and stand-alone options (Energy Sector Management Assistance Program (ESMAP), 2014; Korkovelos et al., 2020; Mentis et al., 2017).

Techno-economic studies using tools such as HOMER Pro provide detailed feasibility results for specific islands or villages, including PV-diesel-battery combinations and sensitivity to fuel cost, load, and storage assumptions (Hutabarat et al., 2025; Kang et al., 2023; Pujiانتara et al., 2024; Rumbayan & Nagasaka, 2018; Subekti et al., 2024). Although these methods are valuable for detailed feasibility assessment, they are often too data-intensive for a first national screening and do not always express rural road-access difficulty as a separate planning layer.

Studies on Indonesia-specific PV also leave a provincial screening gap. Veldhuis and Reiniers (2015) evaluated off-grid PV potential and cost-effectiveness at the provincial level, while later Indonesian studies examined remote microgrids, PV design, hybridization, and island case studies in locations such as Maluku, North Maluku, Lombok, Raja Ampat, East Nusa Tenggara, Miangas, and Pantar Island (Ali et al., 2024; Hutabarat et al., 2025; Kang et al., 2023; Pujiانتara et al., 2024; Rumbayan & Nagasaka, 2018; Simatupang et al., 2021; Subekti et al., 2024; Sulaelman et al., 2021). However, a simple, replicable, province-level framework that jointly screens intervention need, solar resource, road-based implementation difficulty, port sensitivity, and construction-cost burden for rural PV intervention planning has not yet been provided. This is a practical gap for the government and PLN because investment pipelines require pre-feasibility triage before the launch of detailed village-level surveys.

Therefore, three research gaps motivate this study. First, conventional electrification indicators are insufficient because they show connection status but not implementation difficulty or local service quality. Second, conventional RAI is insufficient because it measures road access but not electricity-intervention need, PV suitability, construction cost, or non-PLN reliance. Third, techno-economic PV studies are insufficient for national pre-screening because they usually focus on individual systems or case-study locations after the selection of candidate sites. A screening framework between national policy targets and feasibility studies at the village level is required.

This study develops a provincial screening framework for rural solar PV intervention planning in Indonesia by adapting ARAI as an implementation-difficulty layer. The novelty is not merely the use of RAI in an energy-planning context; rather, it lies in adapting RAI into ARAI as an implementation-difficulty layer and combining rural access, electricity need, solar suitability, port-access sensitivity, and construction-cost burden into one provincial pre-feasibility typology for rural PV planning in an archipelagic country. This contribution is deliberately narrower than a least-cost electrification model or a project-level techno-economic feasibility study: it fills the screening gap between national electrification targets and detailed feasibility assessment of village- or island-level PV. The resulting typology helps identify near-term PV screening candidates, strategic candidates requiring logistics and subsidy support, and provinces where detailed PV-battery-diesel design checks are still required before project prioritization. The framework is needed because planners require an intermediate tool that translates national electrification and geospatial data into a shortlist for district, island, and village surveys. Operationally, the framework separates Intervention Need Score (INS), Solar PV Suitability (SPS), and Implementation Difficulty Score (IDS) before translating their combinations into A-H planning types, so the result indicates practical follow-up actions rather than a province ranking.

In this study, provincial screening is used as pipeline triage: it identifies provinces where detailed district-, island-, or village-level feasibility work should be prioritized, but it does not determine final project sites, system capacities, or investment approval. A lower-priority provincial category may still contain remote islands or villages with urgent needs, and a high-priority province may still contain districts with substantially different access, demand, and solar-resource profiles.

The paper is organized as follows: The Methods section describes the data sources, ARAI scenarios, INS, SPS proxy, IDS, and typology construction. The Results and Discussion section interprets the ARAI sensitivity results, electricity-intervention need, solar suitability, implementation difficulty, and final planning typology. The Conclusions section summarizes the study's contribution and specifies the main limitations that should be addressed in future village- and

island-level studies.

2. Methods

2.1 Study Design and Scope of Analysis

This study develops a provincial screening framework for rural solar PV intervention planning in Indonesia by adapting ARAI as an implementation-difficulty layer. In the framework, ARAI is used as one implementation-difficulty layer rather than a standalone priority index. The analytical unit is the province, whereas the planning target is rural and UDV that may require government or PLN intervention. The framework is intended for early-stage screening, not for final site selection, system sizing, or project feasibility assessment. This positioning follows the logic of geospatial electrification planning, which uses spatial layers to narrow the candidate space before conducting detailed techno-economic optimization or field engineering assessment (Energy Sector Management Assistance Program (ESMAP), 2014; Korkovelos et al., 2020; Mentis et al., 2017). The method estimates ARAI and RAD, constructs INS, SPS, and IDS, and then converts the combined profile into a planning typology for follow-up action.

Figure 1 summarizes the provincial screening framework used to construct the prototype. The framework separates the three planning dimensions. First, INS captures whether public intervention is justified using UDV status, household electricity deficit, non-PLN household reliance, and household scale. Second, SPS captures whether the available solar resource renders PV technically attractive at a screening level. Third, using the RAI-based RAD and CCI, IDS captures the likely logistical and construction burden. This separation follows the principle that energy access is multidimensional and that rural development indicators should not collapse social need, resource potential, and delivery constraints into a single undifferentiated metric (Abreu et al., 2022; Bhatia & Angelou, 2015). Poor access may increase the need for public intervention, but it also increases the difficulty of implementation.

2.2 Data Sources

Where possible, all core planning variables were harmonized to year 2024. The main data layers, primary sources, and analytical roles are summarized in Table 1. The data strategy deliberately combines official Indonesian statistics, open geospatial layers, and internationally recognized solar-resource sources because provincial screening requires reproducibility and national coverage before detailed surveys are available. Operational details, such as road-class selection, rural-mask thresholds, IRI thresholds, and port-buffer sensitivity, are described in the relevant subsections.

2.3 ARAI and RAD

The road-access layer adapted the RAI logic of measuring RP within a 2-km access distance from an all-season road (Iablonovski et al., 2024; Roberts et al., 2006; United Nations, 2024; Workman & McPherson, 2021; World Bank, 2016, 2019). Spatial processing was conducted using open-source QGIS software and selected OpenStreetMap (OSM) regency-road classes. Because condition data are not available for all selected OSM regency roads and the port layer is only a sensitivity addition, the index is interpreted as an ARAI proxy rather than official SDG 9.1.1 RAI.

RP was identified using gridded-population thresholds informed by the degree of urbanization (Degurba) approach, which classifies grid cells according to density, population size and contiguity (European Union et al., 2021). The baseline scenario used grid cells below 300 people/km² and required less than 5,000 people in neighboring cells to exclude urban centers and clusters. A second RP-mask variant used a less restrictive threshold of below 500 people/km² as a sensitivity assumption while retaining the same neighboring-cell population exclusion rule. All scenarios used a 2-km buffer around the selected road network.

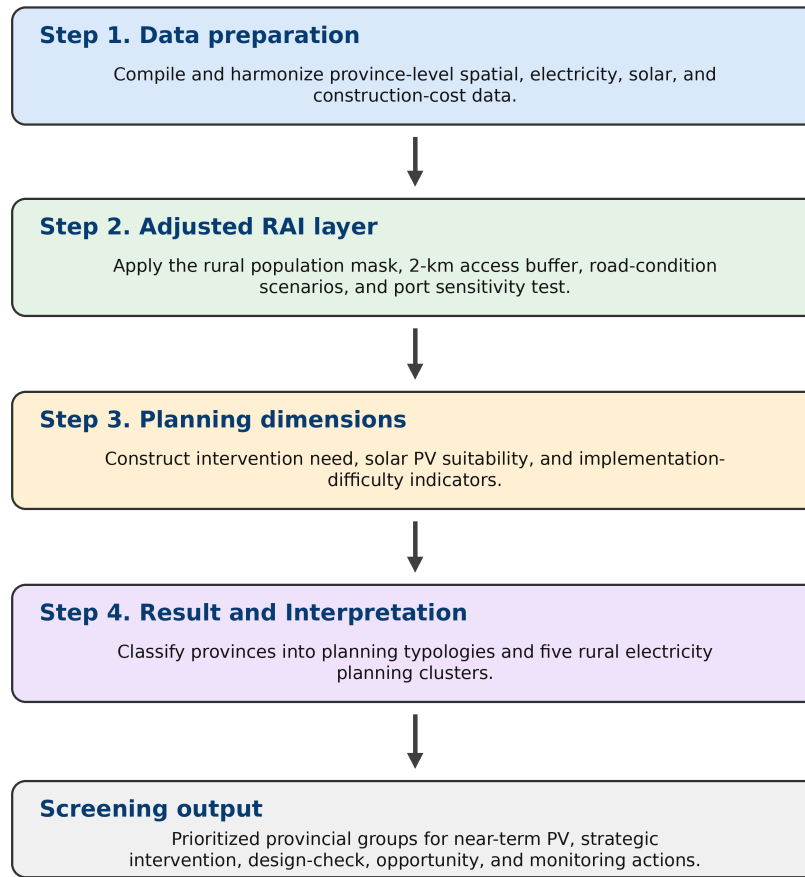


Figure 1 Provincial screening framework for rural solar PV intervention planning

The ARAI, RAD, and unserved RP proxy were calculated as follows:

$$ARAI(p, s) = RP_access(p, s) / RP_total(p, s) \quad (1)$$

$$RAD(p, s) = 1 - ARAI(p, s) \quad (2)$$

$$RP_outside(p, s) = RP_total(p, s) \times RAD(p, s) \quad (3)$$

where p denotes the province and s denotes the scenario; $ARAI(p, s)$ is the ARAI value for province p under scenario s , $RP_access(p, s)$ is the RP located within the selected 2-km buffer of selected accessible roads, and $RP_total(p, s)$ is the total RP after applying the RP mask or excluding urban centers and clusters. $RP_outside$ is a proxy for estimating RP outside the selected 2-km road-access buffer. This variable represents RAD, not the electricity-access deficit. ARAI measures rural road accessibility, whereas RAD measures road-access difficulty. Hence, RAD is more useful than ARAI for the planning framework. Higher RAD means higher deployment difficulty. $RP_outside$ translates access difficulty into the scale of RP that is potentially affected. Therefore, RAD is used as the implementation-difficulty layer in the rural solar PV intervention screening framework.

The study created eight scenarios by varying three assumptions: national-road IRI threshold, RP mask, and access layer (Table 2). Scenario 1, using IRI 0-8, the <300 people/km² RP mask, road-only access, and a 2-km buffer, was retained as the baseline scenario for RAD-based

IDS assessment. The detailed QGIS sequence used for the ARAI calculation is provided in Supplementary Figure S1, while the text and Table 2 explain the technical thresholds, equations, and scenario combinations.

Table 1 Data sources and variables used in the provincial screening prototype

Data layer	Primary source / processing source	Role in framework
ARAI / RAD	Open-source QGIS software using road, RP, port, and boundary layers (Directorate General of Highways, 2024; LapakGIS, 2024; OpenStreetMap Contributors, 2024; QGIS Development Team, 2024)	Baseline ARAI/RAD and sensitivity scenarios
Village infrastructure	Village Potential Statistics (Podes) 2024 (BPS-Statistics Indonesia, 2024b)	Village-incidence context for PLN, non-PLN, and non-electricity family variables
UDV status	Village Development Index (IDM) 2024 (Kemendesa PDTT, 2024)	Government-intervention target layer
Household electrification	Electricity Statistics 2024 (Directorate General of Electricity, 2025)	Household electricity deficit, non-PLN reliance, and load/beneficiary proxy
Solar resource proxy	Remote/farthest-village irradiation values (Energy Sector Management Assistance Program (ESMAP) & Solargis, 2024)	Screening-stage solar PV suitability
CCI	Construction Cost Index (CCI) 2024 (BPS-Statistics Indonesia, 2024a)	Construction-cost component of IDS

2.4 Electricity Intervention Need

The electricity access deficit was defined as a household-level connection deficit. For each province, unelectrified households were calculated from the ESDM household electrification table as total households minus PLN household count (PLN_HH) and non-PLN household count (NPLN_HH). The NPLN_HH was not treated as unelectrified. Instead, it was retained as a separate indicator of decentralized or non-PLN service reliance, which is relevant for de-dieselization, PV hybridization, and rural service-planning discussions because connection status alone does not describe quality, reliability, or long-term service adequacy (Bhatia & Angelou, 2015; International Energy Agency (IEA) et al., 2025).

The INS combined four normalized variables: UDV share, estimated unelectrified-household count (EAD_HH), NPLN_HH, and total households. The INS was calculated using the following min-max normalized variables:

$$\text{INS}(p) = 0.35 \times \text{UDV_norm}(p) + 0.30 \times \text{EAD_HH_norm}(p) + 0.25 \times \text{NPLN_HH_norm}(p) + 0.10 \times \text{HH_norm}(p) \quad (4)$$

where INS denotes the intervention-need score, UDV_norm is the normalized UDV share, EAD_HH_norm is the normalized EAD_HH, NPLN_HH_norm is the normalized NPLN_HH, and HH_norm is the normalized total household count. All variables in Eq. (4) are min-max normalized before weighting.

The INS was constructed as a policy-weighted screening indicator rather than a statistically estimated welfare model. Higher weights were assigned to UDV share and EAD.HH because these variables directly represent the need for public or government intervention. NPLN.HH was assigned a slightly lower weight because it indicates decentralized or non-grid electricity reliance relevant to de-dieselization, but it does not necessarily imply the absence of electricity access. The lowest weight was assigned to the total household count because it represents the intervention scale or potential beneficiary load rather than deprivation itself. Therefore, this weighting structure was used to prioritize provinces where social need and electricity-access deficit are more prominent while preventing large-population provinces from dominating the score solely because of scale.

2.5 SPS Proxy

At this prototype stage, SPS was represented by annual irradiation values extracted from the Global Solar Atlas for selected remote or farthest village/area points in each province. The authors compiled the values into a remote-village irradiation table and used them as a screening-stage proxy for solar resource conditions in intervention-relevant locations (Energy Sector Management Assistance Program (ESMAP) & Solargis, 2024). The solar layer is a screening-stage proxy; therefore, it should be interpreted as a first-order solar attractiveness indicator rather than a site-specific PV yield estimate. Detailed PV-battery-diesel assessment still requires village-level load, PVOUT, storage, diesel, and dispatch assumptions (Hutabarat et al., 2025; Kang et al., 2023; Zebra et al., 2021).

The min-max normalization is used to convert annual irradiation $H(p)$ into a value range 0–1 of SPS score, allowing comparison and combination with other normalized planning indicators. The normalized SPS was calculated as follows:

$$SPS(p) = [H(p) - H_{min}] / [H_{max} - H_{min}] \quad (4)$$

where $SPS(p)$ is the SPS for province p , and $H(p)$ is the annual irradiation proxy value at the most remote-village point in province p . H_{min} is the lowest irradiation value among all provinces, and H_{max} is the highest irradiation value among all provinces. In the gathered processed dataset, $H_{min} = 1,679$ kWh/m²-year and $H_{max} = 2,131$ kWh/m²-year. A higher SPS indicates stronger solar-resource suitability for PV screening.

2.6 Implementation Difficulty

IDS was calculated separately from INS. RAD represents difficulty in physical access. The CCI, reported by the Indonesia Central Bureau of Statistics, represents construction-cost burden. BPS defines CCI as a proxy for the costliness of construction, where higher values indicate higher cost to construct a building or construction work in the relevant area (BPS-Statistics Indonesia, 2024a). This variable is important because remote PV deployment is affected not only by distance to roads but also by local construction markets, material delivery, labor availability, and the cost of civil and electrical works (Energy Sector Management Assistance Program (ESMAP), 2022, 2024). The normalized CCI was combined with the baseline RAD using equal weights:

$$IDS(p) = 0.50 \times RAD_S1(p) + 0.50 \times CCI_norm(p) \quad (5)$$

where IDS denotes the implementation-difficulty score, RAD_S1 is the baseline RAD under Scenario 1, and CCI_norm is the min-max normalized CCI value. Equal weights were assigned to RAD and CCI_norm because no empirical project-cost dataset or expert elicitation was available to support differential weighting at this prototype stage. Therefore, the IDS is interpreted as a neutral screening indicator and not as a calibrated construction cost model. The IDS is a screening-stage implementation-burden indicator rather than a project-cost estimate.

Table 2 ARAI scenario design used for the sensitivity analysis

Scenario	Road condition	Rural mask	Access layer	Purpose
S1	IRI 0–8	<300 people/km ² ; <5,000 neighboring-cell population	Road only	Baseline ARAI
S2	IRI 0–8	<500 people/km ² ; <5,000 neighboring-cell population	Road only	Rural-mask sen- sitivity
S3	IRI 0–12	<300 people/km ² ; <5,000 neighboring-cell population	Road only	Road-condition sensitivity
S4	IRI 0–12	<500 people/km ² ; <5,000 neighboring-cell population	Road only	Combined road condition and rural mask sen- sitivity
S5	IRI 0–8	<300 people/km ² ; <5,000 neighboring-cell population	Road + 2-km port buffer	Port-layer sensi- tivity
S6	IRI 0–8	<500 people/km ² ; <5,000 neighboring-cell population	Road + 2-km port buffer	Port + rural- mask sensitivity
S7	IRI 0–12	<300 people/km ² ; <5,000 neighboring-cell population	Road + 2-km port buffer	Port + road con- dition sensitivity
S8	IRI 0–12	<500 people/km ² ; <5,000 neighboring-cell population	Road + 2-km port buffer	Most inclusive scenario

Consequently, IDS should not be interpreted as a monetary project-cost estimate, capital-expenditure estimate, or levelized-cost estimate. It only indicates the relative implementation burden at the provincial scale; therefore, high-IDS provinces require earlier logistics checking, cost-contingency review, and local constructability assessment before project feasibility or budgeting decisions are made.

A weight-sensitivity test was added to address the judgment-based weighting of Equations (4) and (6). The baseline policy-priority weights for the INS were compared with an equal-weight scenario, assigning 0.25 to each intervention-need variable, and with one-at-a-time $\pm 20\%$ perturbations of UDV_norm, EAD_HH_norm, NPLN_HH_norm, and HH_norm. Each perturbed weight was multiplied by 1.20 or 0.80 and then renormalized so that the total weight remained equal to one. For IDS, the baseline equal weights were compared with an Expert IDS scenario that assigns 0.60 and 0.40 to RAD.S1 and 0.40 to CCI_norm, and with one-at-a-time $\pm 20\%$ perturbations of RAD.S1 and CCI_norm. Rank stability was evaluated using Spearman rank correlation against the baseline, while classification sensitivity was measured as the number of provinces changing planning type or IDS difficulty class.

2.7 Final Planning Typology (FPT)

The final typology classified the provinces using three dimensions: INS, SPS, and RAD. The INS was classified as high or low using the median score. The SPS was classified into low, moderate, and high using tertile thresholds from the normalized SPS. The RAD was classified as high or low using the median baseline RAD. The typology is designed for screening and policy prioritization, not for final PV siting. This classification approach is deliberately transparent because the available data do not justify a calibrated predictive model of project cost or village-

level feasibility. It is closer to a multi-criteria pre-screening instrument than to an optimization model (Abreu et al., 2022; OECD, 2018). External plausibility was assessed through a qualitative validation check using documented rural PV, PV-diesel, and microgrid cases in Indonesia. Each case was mapped to its corresponding province and compared with the planning typology to examine whether known cases of remote electrification fall into categories consistent with their documented implementation context. This check is an external consistency test, not statistical validation because project-level cost, load, and implementation-outcome data are not available for all cases.

3. Results and Discussion

Because the analysis is aggregated at the provincial level, the following results should be read as relative screening evidence rather than deterministic siting outputs. The typology is intended to guide the sequence of follow-up feasibility studies and pipeline triage while recognizing that local inequalities can be hidden within provincial averages. Therefore, the discussion is organized to show why the framework is needed, how the scores behave, which provincial findings are strongest, and how each typology class supports practical PV intervention decisions.

3.1 Results of ARAI and Sensitivity

This subsection answers where rural road access is difficult and which geospatial assumptions affect the provincial ARAI the most. Figure 2 summarizes the baseline spatial distribution of ARAI. Figure 2B shows that Java falls in 40%–60% and 60%–80% classes. Central Java and DI Yogyakarta are higher than much of West Java and East Java. Java has comparatively stronger rural road coverage. Rural PV intervention may result in lower access burden, but the government intervention argument must be based more on need indicators than on remoteness. Sumatra has a mixed pattern as shown in Figure 2A. Aceh, North Sumatra, West Sumatra, Riau, Lampung and Bangka Belitung are mostly around 40%–60%, whereas Jambi, South Sumatra, and Bengkulu appear lower at 20%–40%. RAD remains important in central and southern Sumatra. PV logistics are not as extreme as those in Papua or Maluku, but several provinces still require access-sensitive planning. Kalimantan is mostly 20%–40%, with some provinces reaching 40%–60%. The interior areas remain weakly served. Kalimantan has a clear access-deficit problem as illustrated in Figure 2C. Large land area, forested interiors, and dispersed rural settlement make road-based PV delivery and maintenance more difficult. Sulawesi, as summarized in Figure 2D, is mostly 40%–60%, with North Sulawesi appearing higher and West Sulawesi lower. Overall, Sulawesi has moderate rural road access but uneven access. Coastal and corridor-based access may be acceptable, whereas interior and mountainous areas remain difficult to serve.

Figure 2G shows that Papua is mixed but generally access-constrained. Several provinces fall in the 20%–40% or 40%–60% classes, with sparse road network coverage. Papua is a region with high-difficulty implementation. Even where the provincial color appears moderate, road continuity and settlement dispersion imply that village-level feasibility checks are essential before PV deployment.

The setting in islands provinces is slightly different. Bali and NTB (Figure 2E) are mostly 40%–60%, whereas NTT is largely 20%–40%. NTT stands out as a strategic rural PV intervention area, with a strong solar resource, but a substantial rural access deficit. This supports the need for logistics-aware PV planning. Maluku and North Maluku in Figure 2F show fragmented island access, mostly 20%–60% depending on the province. RAI alone is structurally limited in archipelagic provinces. Maritime access and port proximity are important sensitivity variables because road access cannot fully represent inter-island logistics.

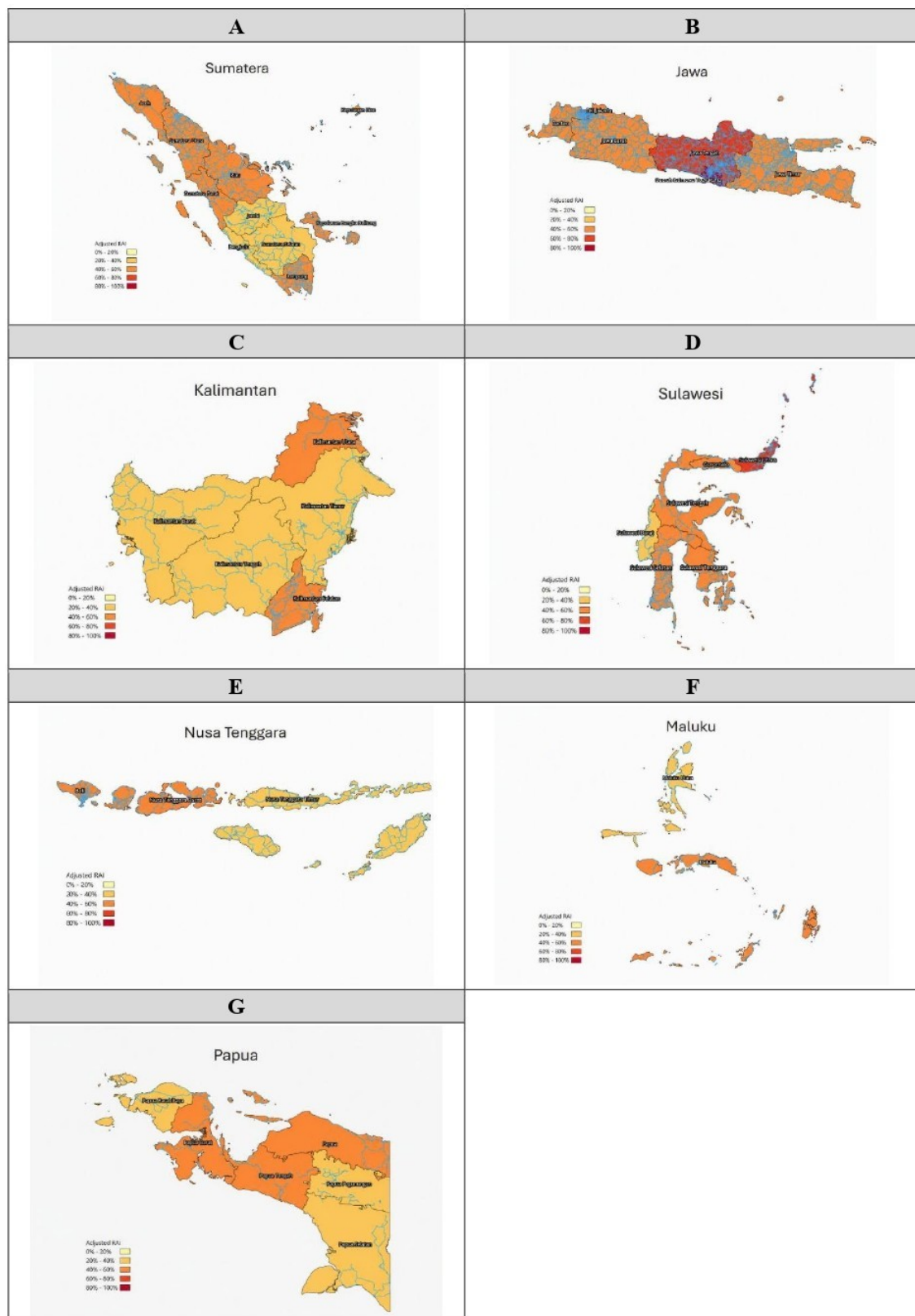


Figure 2 Baseline ARAI maps by island group under Scenario 1. (A) Sumatera Island. (B) Java Island. (C) Kalimantan Island. (D) Sulawesi Island. (E) Nusa Tenggara Islands. (F) Maluku Islands. (G) Papua Island

The overall pattern in the baseline maps shows that rural road access in Indonesia is highly uneven. Java and parts of Sulawesi and Sumatera show relatively higher RAI values, whereas Kalimantan, Nusa Tenggara, Maluku, and Papua show stronger access constraints. This is consistent with the archipelagic and frontier geography of Indonesia: road density and road continuity are much stronger in densely populated islands than in remote, mountainous, forested, or island-fragmented regions. These patterns confirm that rural solar PV intervention planning should not rely solely on electrification indicators or solar resource availability. Road accessibility must be treated as an implementation-difficulty layer because it affects the delivery, construction, operation, and maintenance of equipment. This finding is consistent with the literature on rural access and remoteness, which shows that transport access, population distribution, and distance to service centers shape development feasibility, not merely administrative rural status (Iablonovski et al., 2024; Statistics Canada, 2023; Workman & McPherson, 2021).

The sensitivity test was designed to determine whether the national-road IRI threshold, RP mask, or the addition of port access had the largest effect on the ARAI result. The ARAI sensitivity test across the eight scenarios defined in Table 2 is summarized in Figure 3. Figure 3A shows the national/provincial average ARAI under the eight scenarios. The mean ARAI ranges from 45.8% in the S1 baseline to 53.0% in the S8 most inclusive scenario. This means that when the assumptions become more inclusive, more RP is classified as having proximity to a road or access. Scenarios with a broader RP mask tend to produce much higher ARAI values. The road-only and road-plus-port scenarios are close to each other, meaning that the port layer adds some access but does not radically change the national pattern.

Figure 3B shows the average effect of each assumption. The RP mask has the largest effect, the port layer has a small effect, and the road condition has a negligible effect. The RP definition is the most important because it changes the denominator and spatial population mask. When the rural definition is expanded from less than 300 people/km² to less than 500 people/km², more semi-rural, peri-rural, or urban-cluster population cells enter the calculation. Many of these cells are closer to roads; therefore, ARAI increases. On average, the port layer adds less than one percentage point. This does not mean that ports are unimportant. This means that at the provincial scale, a 2-km port-access layer only modestly changes the classification of access. Port access may matter more at the island or village scale. The IRI threshold has the smallest effect. Expanding the national road condition from IRI 0–8 to IRI 0–12 barely changes ARAI. It means that the national-road condition threshold is not the dominant uncertainty in the current dataset.

Figure 3C uses Spearman's rank correlation against the S1 baseline. This checks whether provinces maintain roughly the same relative ranking when assumptions change. When the IRI changes (S1-S3), the ranking remains unchanged. Similarly, when port layer changes (S1-S5), the ranking is almost unchanged. However, when the RP mask changes (S1-S2), the ranking changes moderately. Equally, in the most inclusive scenario (S1-S8), the ranking changes moderately. This means that the provincial ranking is highly stable when only the IRI threshold or port layer changes. However, the ranking becomes less stable when the RP mask is changed. This means that the largest uncertainty is not road condition or port inclusion but how RP is defined and spatially masked.

For rural solar PV intervention planning, this figure supports three conclusions. The baseline ARAI is not overly fragile. The results remain broadly stable under the IRI and port assumptions. Second, the RP mask must be clearly explained because it materially affects the RAI value and provincial ranking. This confirms the warning in recent RAI and rural classification studies that the definition of RP can materially influence spatial access estimates (European Union et al., 2021; Iablonovski et al., 2024; Sun et al., 2023; Workman & McPherson, 2021). Third, the use of ARAI as an implementation-difficulty layer is defensible; however, the scenario range should be interpreted as a sensitivity envelope rather than a single official access estimate.

In summary, the sensitivity analysis indicated that the ARAI results were most affected by the RP mask. Expanding the RP mask from less than 300 to less than 500 people/km²

increases mean ARAI by 6.16 percentage points, while the port-access layer and IRI threshold changes increase the mean ARAI by only 0.82 and 0.24 percentage points, respectively. Spearman's rank correlations against the baseline scenario show that provincial rankings remain highly stable under the IRI and port assumptions, but are more sensitive to the RP mask. This confirms that the RP definition is the dominant methodological assumption in the ARAI calculation. The province-level implication is that low-ARAI provinces should be treated as high-implementation-difficulty screening contexts rather than low-priority regions. The most constrained baseline group included West Kalimantan, South Sumatera, Central Kalimantan, South Papua, West Sulawesi, Highland Papua, Bengkulu, Jambi, Southwest Papua Barat Daya, and East Kalimantan.

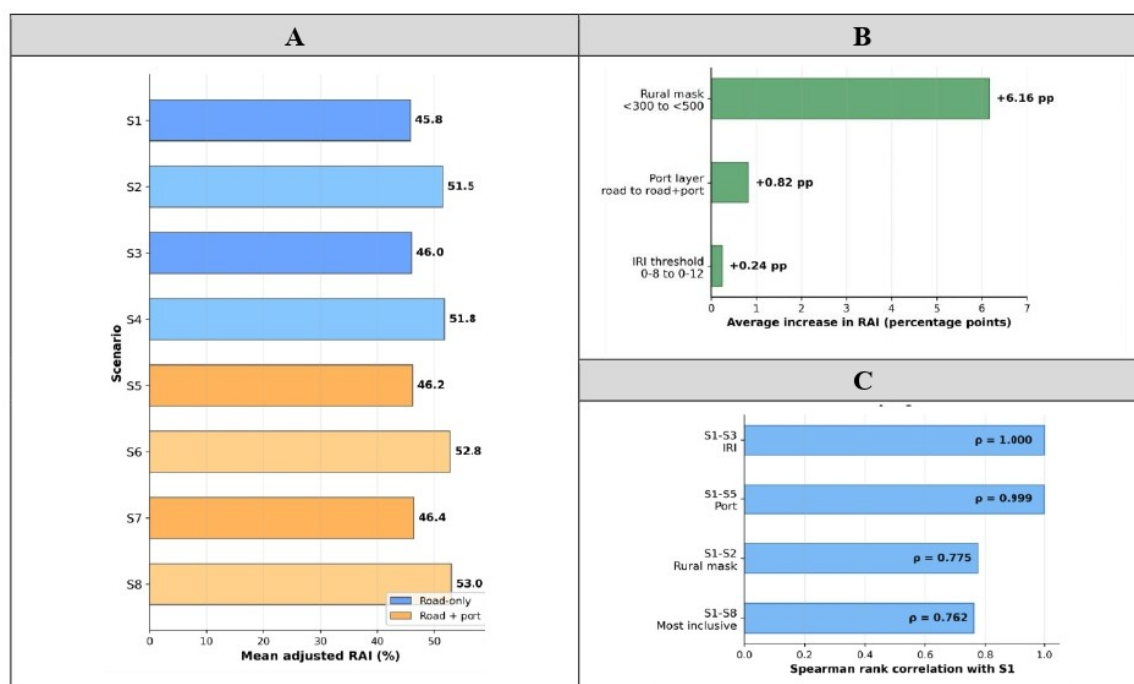


Figure 3 Statistical summary of the ARAI results and sensitivity across the eight scenarios. (A). Mean adjusted RAI by scenario. (B) Average scenario effect. (C). Rank stability against baseline.

3.2 Need for Electricity Intervention and Household-Scale Deficit

This subsection identifies where government or PLN intervention is justified from the perspective of electricity access. The ESDM household electrification table provided the strongest available household-level electricity deficit variable in the gathered data. The processed table implies 150,490 unelectrified households in 2024, whereas the broader PLN service-gap proxy includes both unelectrified and non-PLN households. East Nusa Tenggara has the largest EAD_HH in the processed dataset, followed by East Java, Central Kalimantan, Highland Papua, and Central Papua. The presence of East Java in this list should not be misread as a remote-rural access problem of the same kind as Papua or Kalimantan. East Java has a huge household base; therefore, even a small percentage deficit can produce a large absolute number. This reinforces the need to report both intensity and absolute beneficiary-scale variables.

3.3 The Solar PV Suitability Proxy

This subsection assesses whether solar photovoltaic (PV) is technically reasonable at the provincial screening stage. The proxy for remote-village irradiation produced normalized SPS

values between 0 and 1. The highest SPS values were found in East Nusa Tenggara, West Nusa Tenggara, Bali, and East Java. South Sulawesi, West Sulawesi, Southeast Sulawesi, and Central Papua also showed moderate-to-high values. Low values in parts of Sumatera and Kalimantan do not imply that PV is infeasible; however, they indicate that PV design and capacity requirements should be carefully checked. This interpretation is consistent with Indonesia-specific studies showing that solar PV and PV-diesel-battery systems can be attractive in remote areas, but final feasibility is highly sensitive to load, diesel cost, storage sizing, and resource assumptions (Hutabarat et al., 2025; Pujiantara et al., 2024; Rumbayan & Nagasaka, 2018; Subekti et al., 2024; Veldhuis & Reinders, 2015). The proxy is defensible for the current screening stage because the selected locations are closer to the rural intervention target than provincial capitals.

3.4 Implementation Difficulty from RAD and CCI

IDS combines baseline RAD and CCI to indicate the areas where logistics and construction burdens are highest. The highest scores occurred in Highland Papua, Central Papua, South Papua, West Kalimantan, Central Kalimantan, Southwest Papua, and East Kalimantan. These provinces should not be interpreted simply as low-priority areas; rather, they represent places where stronger logistics planning and higher implementation support may be required for public intervention.

The use of CCI improves the implementation-difficulty layer because road access alone cannot capture the price of materials, labor, and construction services. However, IDS remains a high-level screening indicator. It excludes maritime transport tariffs, seasonal passability, actual travel time, terrain-specific transport cost, contractor availability, and battery logistics. This limitation is important because the literature on remote mini-grids and island systems shows that lifecycle costs and service reliability depend not only on initial access or solar resources but also on fuel logistics, spare parts, O&M capability, battery replacement, and institutional arrangements (Babayomi et al., 2023; Energy Sector Management Assistance Program (ESMAP), 2024; Sulaeman et al., 2021; Zebra et al., 2021).

Therefore, for planning, high-IDS provinces should therefore be treated as locations requiring additional preparatory work before detailed PV feasibility modeling. Follow-up assessment should verify road passability, transport routes, contractor availability, battery and equipment delivery constraints, O&M access, and possible cost contingencies. Conversely, a lower IDS should be read only as a lower relative access and construction burden at the provincial scale, not as an automatic project feasibility.

3.5 Final Planning Typology (FPT)

The final typology assigns each province to a planning class by combining intervention need, solar potential, and RAD. Supplementary Figure S2 illustrated a combined visualization of the detailed numerical tables. It summarizes the final provincial screening results. It does not present exact feasibility results; instead, it visualizes each province's relative planning profile using normalized indicators from 0 to 1. The figure combines four dimensions: INS (Need), SPS (Solar), RAD (Road), and IDS (Diff). Higher Need means stronger need for public (government/PLN) intervention. Higher Solar means better solar resources in remote areas. Higher RAD means harder road-based access and logistics. A higher Diff indicates a higher combined access and construction burden. On the basis of these four dimensions, provinces are translated into planning types that indicate the follow-up action required rather than an absolute investment ranking.

Type A represents candidates for near-term screening. These provinces combine a relatively high need for intervention, acceptable or strong solar suitability, and moderate RAD. They are the most suitable for near-term screening, meaning they can be prioritized for further provincial or district-level pre-feasibility assessment.

Type B represents strategic candidates requiring logistics and subsidy support. These are

strategically important. They have strong intervention relevance and generally favorable solar potential, but the RAD or implementation burden remains high. These provinces should not be treated as easy projects for rural solar PV planning. They may require a higher logistics budget, stronger subsidy justification, staged deployment, local maintenance arrangements, and possible PV-battery-diesel hybrid design rather than simple standalone PV assumptions.

Type C represents the need-first areas requiring PV design checking. These provinces show intervention need and access difficulty, but solar suitability in the current remote-village proxy is lower or more moderate. This group requires a more careful village-level analysis of: PVOU or Global Solar Atlas raster values, battery sizing, diesel backup requirement, terrain and transport conditions, and actual household demand.

Type D represents solar-opportunity provinces with weaker social priority for targeted rural intervention. These provinces show stronger solar suitability or manageable access but lower need for intervention in this framework. They may be good for: rooftop PV; commercial or institutional PV, grid-connected PV, and general solar programs. However, if the objective is to prioritize underdeveloped or underserved rural areas, they are not the strongest targets for government-funded rural PV intervention.

Type E represents a lower priority for targeted rural PV intervention. These provinces have a relatively lower need for intervention and/or weaker solar suitability while still showing access constraints in some cases. Although local pockets of need may still exist, provincial-scale prioritization is weaker.

Type F indicates that a need exists, but the profile requires further checking. These provinces show some intervention-need signals, but the overall profile does not neatly fit into the main A–E categories. For example, Papua and West Papua may have serious challenges in rural access and electricity, but provincial aggregation can hide very sharp local differences. These provinces require village- or district-level follow-up before drawing strong investment conclusions.

Type H represents the lower urgency / monitoring group. These provinces show weaker combined priority under the current provincial framework. They may still have remote islands or local underserved communities, but at the provincial level, they do not emerge as high-priority targets compared with the strategic groups.

The combined typology demonstrates that rural solar PV intervention planning should not rely on a single indicator. Provinces with high solar resources are not automatically the strongest public-intervention targets, and provinces with high RAD are not automatically PV priorities. The strongest candidates are those in which the intervention need, solar suitability, and implementation difficulty are jointly considered. This result complements previous Indonesian provincial and case-study PV analyses by adding a national screening layer before detailed island- or village-level feasibility assessment (Hutabarat et al., 2025; Veldhuis & Reinders, 2015). The key message is that Type A provinces can move first to candidate-site screening, Type B provinces require logistics and subsidy preparation before implementation, and Type C or Type F provinces require stronger PV-battery-diesel design checks before prioritization.

In practical pipeline triage, Type A provinces should be studied first through district- and village-level candidate screening because they combine intervention need, solar suitability, and relatively manageable access burden. Type B provinces should be treated as strategic public-intervention candidates, but their follow-up studies should begin with logistics planning, subsidy justification, delivery-route assessment, and staged implementation design. Type C and Type F provinces require technical PV-battery-diesel design checks and stronger local data before prioritization because either solar suitability or access conditions are less straightforward. Type D provinces are more suitable for general solar development programs, rooftop PV, institutional PV, or grid-connected PV opportunities than for targeted UDV intervention. Type E and Type H provinces should remain in routine monitoring, while subprovincial screening is still needed to identify isolated pockets of urgent need that may be hidden by provincial averages.

3.6 Qualitative Validation against Documented Rural PV and Microgrid Cases in Indonesia

The final typology was compared with documented Indonesian rural PV, PV-diesel, and microgrid cases to strengthen the external plausibility of the framework. Supplementary Table T1 provides a detailed case comparison; the main text retains the interpretation needed to assess whether the provincial typology is consistent with known remote electrification contexts.

The comparison shows reasonable external consistency. Pantar Island, Raja Ampat, and North Maluku are located in strategic or design-check categories, while Lombok and Miangas illustrate the expected limitations of provincial aggregation. These partial mismatches are not framework failures; they confirm that the typology should be used for provincial pipeline triage and followed by feasibility studies at the island or village level. This validation result strengthens the paper by showing that the typology is plausible against known Indonesian cases while avoiding the stronger claim of statistical validation.

3.7 Weight-Sensitivity Robustness of the Proposed Weighting Scheme

The practical implication is that rural PV prioritization should not be reduced to a single score. Figure 4 presents the weight-sensitivity robustness test used to evaluate whether the judgment-based weights strongly influence the final screening result.

Figure 4A shows that all alternative weighting scenarios remain strongly correlated with the baseline ranking. The equal-weight INS scenario produces the lowest but still strong rank correlation ($\rho = 0.949$), whereas the Expert IDS scenario reaches $\rho = 0.984$ and the $\pm 20\%$ perturbations of UDV share, EAD_HH, NPLN_HH, total households, RAD, and CCI remain approximately within $\rho = 0.992$ –1.000. This indicates that a single arbitrary weight does not drive provincial ordering.

Figure 4B shows that the final planning type is stable under changes in intervention-need weighting. Equal INS changes the planning type of only four provinces, while the individual $\pm 20\%$ perturbations of UDV share, EAD_HH, NPLN_HH, and total households do not change any planning type. The IDS difficulty class is more sensitive: the Expert IDS scenario changes eight provinces, the CCI perturbation changes up to six provinces, and the RAD perturbation changes up to four provinces.

These results indicate that the final planning typology is robust to INS-weight assumptions, whereas the IDS layer is more sensitive to the RAD and construction cost balance. Therefore, the class changes should be interpreted as threshold effects around intermediate implementation-difficulty categories and not as instability of the overall provincial screening framework. Accordingly, the weighting scheme is acceptable for provincial pre-feasibility screening, but the IDS layer remains a relative implementation-burden proxy rather than a calibrated project-cost model.

3.8 Interpretation and Limitations of Planning

The typology's planning value converts the screening result into differentiated follow-up actions rather than a single province ranking. The A-H types describe operational implications in the preceding subsection, while Figure 4 provides methodological support that these typology results are not highly sensitive to reasonable weighting changes. Accordingly, the manuscript retains the main planning interpretation in the Results and Discussion: Type A and Type B provinces are the strongest candidates for near-term or strategic follow-up; Type C and Type F provinces require more detailed PV-battery-diesel and local-access checks; Type D provinces are better read as general solar-opportunity areas; and Type E or Type H provinces require monitoring and sub-provincial screening rather than immediate province-wide prioritization.

The limitations are methodological rather than incidental. The processed dataset does not include village-level PVOU, complete road surface and passability data for all OSM roads, village-level household demand, diesel-generation cost, outage records, and maritime logistics data. Provincial aggregation also limits the final project siting and capacity sizing results.

Therefore, the output should be used as a provincial screening prototype that indicates where detailed PLN or government feasibility work should begin, not as a final site-selection or techno-economic design model. The next methodological step should link this screening output with island- or village-level simulation using PVOUT/GHI rasters, measured demand, road passability, port-route data, diesel price, storage replacement, and O&M assumptions. Therefore, the qualitative validation should be read as an external consistency check rather than a project-level feasibility proof. Consequently, no province classified as having no intervention need should be interpreted as having no intervention need; rather, such provinces require more targeted sub-provincial screening to identify isolated remote pockets.

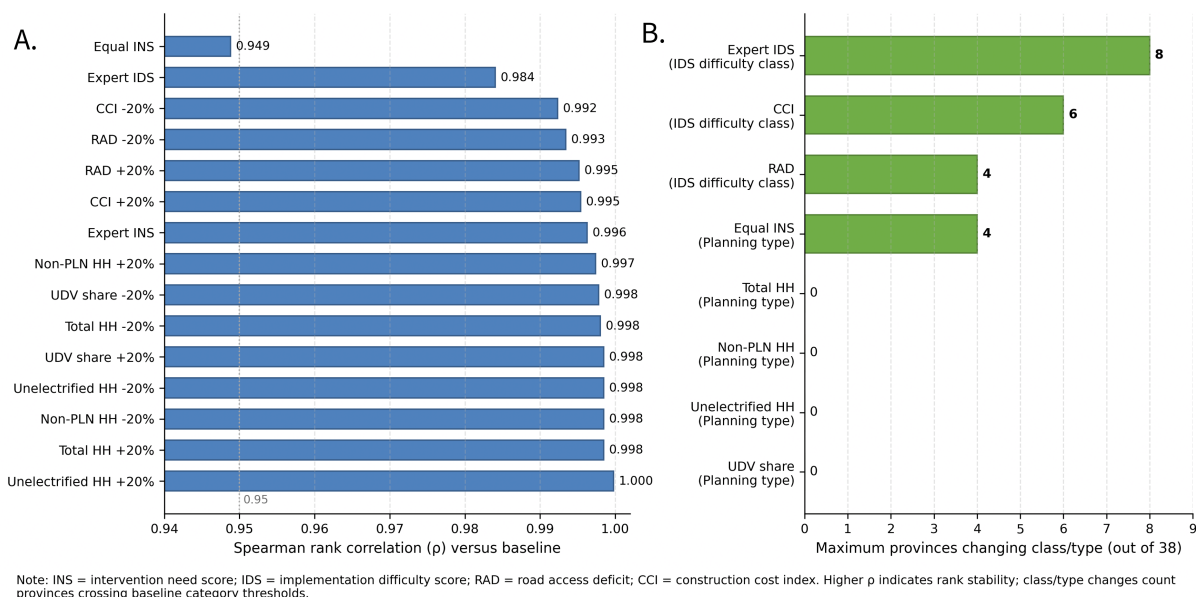


Figure 4 Weight-sensitivity robustness of the provincial screening framework. (A). Rank stability under alternative weights. (B). Classification sensitivity

4. Conclusions

This study developed a provincial screening framework for rural solar PV intervention planning in Indonesia by adapting ARAI as an implementation-difficulty layer. The framework combines ARAI-based RAD, UDV status, household electricity deficit, non-PLN household reliance, remote-village irradiation proxy, port-access sensitivity, and CCI. The main contribution of this study is a provincial pre-feasibility typology that integrates rural access, electricity need, solar suitability, and construction-cost burden for rural PV planning in an archipelagic country; it is not a final PV siting model or a calibrated project-cost model. This framing clarifies that the study extends RAI for implementation-difficulty screening while retaining detailed village-level feasibility assessment as the next required step. The ARAI results indicate how rural road access remains materially constrained under the 2-km buffer approach. The mean baseline ARAI is 0.458, whereas the most inclusive scenario reaches only 0.530. The sensitivity analysis indicates that the RP mask affects the result more than the national-road IRI threshold. The household electricity layer shows that the remaining EAD_HH deficit is concentrated in provinces such as East Nusa Tenggara, East Java, Central Kalimantan, Highland Papua, and Central Papua, while non-PLN household reliance is especially large in Highland Papua, Central Papua, Riau, East Nusa Tenggara, and West Kalimantan. The weighting robustness test confirms that the final planning typology remains stable under equal-weight and $\pm 20\%$ intervention-need perturbations, although IDS is more sensitive to the RAD-CCI weighting balance. Qualitative comparison with documented Indonesian rural PV and microgrid cases further supports the external plausibility of the typology while confirming that provincial aggregation can mask local

island-level intervention needs. In practical terms, the strongest screening outcome is not a universal “best-province” ranking but a differentiated action map showing where to screen first, where to prepare logistics and subsidy support, and where to require design checking before PV intervention.

Conflict of Interest

The authors declare no conflicts of interest.

Supplementary Materials

Supplementary figures and tables are enclosed.

Declaration of AI

AI-assisted tools were used to support language editing, formatting, and document preparation. The authors reviewed and approved the analysis, interpretation, and final manuscript content.

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