

Original Article

Human Capital and Urban-Rural Income Disparities in Samar Province

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Article History:

Date received: June 18, 2026
Date revised: August 23, 2026
Date accepted: September 4, 2026

Recommended citation:

Orongan, J. (2026). Human capital and urban-rural income disparities in Samar Province. *Journal of Interdisciplinary Perspectives*, 4(10), 127-136.
<https://doi.org/10.69569/jip.2026.375>

Abstract. This study examined the role of educational attainment in local government unit-level urban-rural income disparities in Samar Province, Philippines. Addressing limited within-province spatial evidence on local inequality, it analyzed all 26 local government units using an area-level GIS-based and statistical design. The study constructed a relative household-income capacity proxy, an Educational Attainment Index, an Infrastructure Access Index, and an urban-rural location variable from Philippine Statistics Authority and National Mapping and Resource Information Authority data. Descriptive maps, Pearson correlations, and hierarchical regression were used to compare area-level patterns. Results showed spatially uneven income-capacity scores, with higher values generally appearing in city and service-linked local government units. Educational attainment had the strongest association with the income proxy ($r = .64$, $p < .001$). Geographic location explained $R^2 = 0.28$ of the variance, and adding educational attainment increased explained variance to $R^2 = 0.45$. Adding infrastructure produced little additional explanatory gain. The findings suggest that education is the strongest observed statistical factor in the local government unit-level model. However, its income relevance depends on infrastructure functionality, institutional support, labor-market absorption, and local livelihood conditions. The study contributes a cautious spatial-development perspective: human capital can support income capacity when connected to place-specific economic opportunities rather than treated as a stand-alone solution.

Keywords: Educational attainment; Income disparity; Local government units; Samar Province; Spatial analysis.

Urban-rural income disparity remains one of the most persistent forms of inequality in developing economies. In the Philippines, the issue is not merely a difference between city and countryside; it is a spatial development problem in which employment opportunities, education, services, markets, and infrastructure are unevenly distributed across local territories. Philippine studies show that spatial income differences are linked to uneven endowments, regional development patterns, and the distribution of opportunities across provinces and localities (Chua et al., 2015; World Bank, 2022; Pagaduan, 2023).

The literature increasingly treats inequality as spatially organized rather than randomly distributed. Spatial studies on the Philippines and Eastern Visayas indicate that poverty and income conditions tend to cluster across municipalities and are shaped by accessibility, transport networks, service availability, and local development capacity (Pantolla & Atibagos-Nacion, 2023; Leyso & Umezaki, 2024). Regional poverty and inequality research

also shows that growth and redistribution outcomes differ across Philippine regions, reinforcing the need to examine inequality through territorial rather than purely national averages (Capuno, 2022). These findings justify analysis at a local government unit scale because provincial averages can conceal territorial differences among cities, mainland municipalities, coastal communities, island municipalities, and interior areas.

Education is central to this problem because it functions as both an individual capability and a territorial development asset. Human-capital and education-inequality studies show that schooling affects income capacity through productivity, credentials, employability, and occupational mobility (Psacharopoulos & Patrinos, 2018; Akita et al., 2024; Ramirez Yee, 2024). In the Philippine context, education and skill endowments are repeatedly identified as major contributors to urban-rural income and wage gaps, while recent regional analysis also finds college-educated workers to be statistically relevant in explaining intra-regional income outcomes (Chua et al., 2015; Zamora & Dorado, 2015; Habana & Choi, 2024).

This article is guided primarily by Human Capital Theory and spatial inequality perspectives. Human Capital Theory frames the Educational Attainment Index as a local measure of human-capital stock, where higher educational attainment is expected to improve employability, productivity, and income capacity (Becker, 1964; Psacharopoulos & Patrinos, 2018). However, the theory is treated critically rather than mechanically. Education does not automatically translate into income where local labor markets are thin, job opportunities are spatially concentrated, or acquired credentials do not match available employment. This limitation is important because human-capital explanations can overstate the direct education-to-income pathway and understate structural barriers in the labor market (Marginson, 2019). Thus, in Samar Province, education is examined not as an individual guarantee of higher earnings but as a local government unit-level capacity that may strengthen or weaken depending on spatial access, labor absorption, and institutional conditions.

Spatial inequality perspectives frame income disparity as a territorially organized development outcome. From this perspective, poverty and income differences cluster geographically because public services, employment centers, transport networks, schools, health facilities, and institutional capacity are unevenly distributed across places (Pagaduan, 2023; Pantolla & Atibagos-Nacion, 2023; Leyso & Umezaki, 2024). Geographic location is therefore not treated merely as a rural-urban label but as a spatial condition that shapes access to opportunities. This framing supports GIS mapping and local government unit-level analysis because the study seeks to identify where income-proxy, education, and infrastructure differences are concentrated and how these territorial differences relate to one another.

Infrastructure is interpreted through a conditional-access lens. Roads, transport access, digital connectivity, water systems, schools, and health facilities may expand mobility and service access. However, their effects depend on whether they are functional, institutionally supported, and connected to productive livelihood systems. Infrastructure investment may fail to reduce inequality when facilities are incomplete, poorly maintained, weakly linked to markets, or disconnected from local residents' skills and livelihood base (Nugraha et al., 2020; Medeiros et al., 2022; Guo et al., 2024). This is why the model retains infrastructure as an enabling condition rather than assuming it automatically predicts income-proxy improvement.

Samar Province provides a relevant case because it contains urban-classified local government units, rural municipalities, coastal settlements, interior areas, and development corridors with uneven access to markets and services. Existing studies have examined Philippine urban-rural income gaps, regional poverty, education inequality, and spatial access separately. However, fewer studies integrate these dimensions at the within-province local government unit level. This study addresses that gap by testing whether educational attainment remains a salient area-level factor after accounting for geographic location and infrastructure access together.

The study contributes to spatial inequality research and provincial policy by showing how education, geography, and infrastructure interact in a predominantly rural province. Geography shapes access distribution; education influences residents' and localities' capacity to convert access into income; and infrastructure enables mobility and service reach but does not guarantee economic conversion. The present study therefore prioritizes education as the central explanatory layer while retaining geography and infrastructure to test whether human capital remains relevant after accounting for spatial location and access conditions.

Specifically, this study aimed to: (1) describe the spatial distribution of the local government unit-level income

proxy, Educational Attainment Index, and Infrastructure Access Index across Samar local government units; (2) determine the relationship between educational attainment and the income proxy after accounting for geographic location; and (3) examine whether infrastructure access adds explanatory value beyond geographic location and educational attainment.

Methodology

Research Design

The study used a quantitative, cross-sectional, ecological spatial-analytical research design covering all 26 local government units of Samar Province ($N = 26$). It is quantitative because the article analyzes numerical local government unit-level indicators; cross-sectional because the variables are treated as a comparative snapshot using the latest available and comparable official datasets; ecological because the unit of analysis is the local government unit rather than individual households; and spatial-analytical because GIS mapping was used to examine the territorial distribution of the income proxy, education, and infrastructure. This design is aligned with the article version of the manuscript, which reports the secondary-data spatial and statistical component of the thesis rather than the full explanatory sequential mixed-methods design.

Study Area and Unit of Analysis

The unit of analysis was the local government unit. The study covered all 26 local government units of Samar Province, Philippines, through complete enumeration rather than sampling. This was appropriate because the purpose was to compare the full provincial local government unit system and identify spatial differences across cities, urban-classified municipalities, rural mainland municipalities, island municipalities, and interior or upland municipalities. The analysis therefore describes relative local government unit-level conditions, not household-level income behavior.

Variables and Data Sources

The dependent variable was the local government unit-level Relative Average Annual Household Income Proxy. The proxy was constructed from four municipal-level indicators: poverty incidence (2023), average household size (2020), National Tax Allotment per capita (2023), and percent urban (2020). Poverty incidence and average household size were reverse-coded because higher values indicate weaker income capacity, while National Tax Allotment per capita and percent urban were positively coded. These variables were combined because no official, uniformly comparable municipal-level household income series was available for all Samar local government units; together, the indicators approximate relative income capacity through poverty condition, household demographic pressure, fiscal resource capacity, and urban concentration.

$$\text{Income Proxy}_i = [-Z(\text{Poverty}_i) - Z(\text{Household Size}_i) + Z(\text{NTA per Capita}_i) + Z(\text{Percent Urban}_i)] / 4 \quad (1)$$

The resulting values were rescaled to a 0-100 comparative index and interpreted only as relative household-income capacity, not as actual household income in pesos.

The main explanatory variable was the Educational Attainment Index, derived from adult educational attainment distributions based on the 2020 Census of Population and Housing (Philippine Statistics Authority, 2022). Attainment categories were coded from 0 to 5, where 0 represented no formal schooling, 1 elementary, 2 secondary, 3 vocational or technical, 4 tertiary, and 5 postgraduate education. The index was computed as a weighted average of attainment-category percentages for each local government unit, consistent with ordinal approaches to measuring educational attainment (Dumas & Silber, 2021).

$$\text{EAI}_i = (0P_{0i} + 1P_{1i} + 2P_{2i} + 3P_{3i} + 4P_{4i} + 5P_{5i}) / 100 \quad (2)$$

where EAI_i is the Educational Attainment Index of local government unit i , and P_{0i} to P_{5i} are the percentage shares of adults in the corresponding attainment categories.

Geographic location was coded using official urban-rural classification as the baseline spatial variable. Infrastructure access was represented by a Principal Component Analysis-based composite index derived from standardized indicators of waterworks access, road access, connectivity access, school access, and health access. The first principal component was retained because it captured the greatest common variance across the infrastructure indicators; the resulting component scores were used as the Infrastructure Access Index.

$$IAI_i = PC1[Z(\text{Waterworks}_i), Z(\text{Road}_i), Z(\text{Connectivity}_i), Z(\text{School}_i), Z(\text{Health}_i)] \quad (3)$$

Geographic boundary and base-map layers were prepared using official geospatial data and QGIS (National Mapping and Resource Information Authority, 2024; QGIS Development Team, 2024). Table 1 summarizes the operational definitions used in the article.

Table 1. *Operational Definition of Variables*

Variable	Operational definition	Role in analysis
LGU-level relative household-income proxy	Composite proxy score derived from poverty incidence (2023), average household size (2020), NTA per capita (2023), and percent urban (2020). Poverty incidence and average household size were reverse-coded; all four components were standardized, averaged, and rescaled to 0-100.	Dependent variable
Educational Attainment Index	Weighted LGU-level profile based on adult educational attainment categories, coded from 0 (no formal schooling) to 5 (postgraduate), then summarized as a weighted average for each LGU.	Main explanatory variable
Geographic location	Urban-rural classification used as a binary spatial variable (urban = 1, rural = 0). It represents the baseline settlement/location condition of each LGU.	Baseline spatial variable
Infrastructure Access Index	PCA-based index using the first principal component of standardized LGU-level indicators covering waterworks, road access, connectivity, school access, and health access.	Secondary explanatory variable

Data Gathering Procedure

The researcher consolidated local government unit-level secondary data from official datasets of the Philippine Statistics Authority and geospatial boundary data from the National Mapping and Resource Information Authority (Philippine Statistics Authority, 2022, 2024; National Mapping and Resource Information Authority, 2024). The indicators were encoded into a unified data matrix, checked for consistency in local government unit names, matched to spatial boundary layers, and screened for completeness and comparability across all 26 local government units. Completeness meant that each indicator had available values for every local government unit included in the analysis; comparability meant that the indicator was officially sourced, consistently defined across local government units, and usable at the same municipal/city level of aggregation. Although the datasets covered different reference years, 2020 indicators were used for structural census-based variables and 2023 indicators were used for the latest available poverty and fiscal indicators. The combined dataset was therefore interpreted as a recent comparative cross-sectional profile, not as a single-year time-series dataset.

Data Analysis Procedure

Descriptive statistics summarized the distribution of the income proxy, Educational Attainment Index, Infrastructure Access Index, and geographic location variable. GIS mapping visualized the spatial distribution of the three core indices. Pearson correlation analysis tested the bivariate associations among the variables. Hierarchical blockwise regression then examined whether educational attainment and infrastructure access added explanatory power beyond geographic location. Model 1 entered geographic location only; Model 2 added the Educational Attainment Index; and Model 3 added the Infrastructure Access Index. Model performance was assessed using R^2 , adjusted R^2 , R^2 change, F -change, and p -values, with interpretation limited by the data's ecological and cross-sectional nature.

Because the analysis used a complete enumeration of Samar local government units ($N = 26$), inferential statistics were interpreted descriptively and heuristically rather than as estimates intended to generalize to a larger sampling frame. The small number of area-level units also limits regression stability, particularly in the final model with three predictors. Regression diagnostics were therefore treated as screening checks, including inspection of

linearity and residual patterns, multicollinearity, and influential observations, rather than as grounds for strong causal or predictive claims.

Ethical Considerations

The article version used aggregated secondary data from official and publicly accessible sources. No individual-level personal data were collected, and no human participants were recruited for this article version of the study. The analytical dataset did not contain names, addresses, or personally identifiable information. The manuscript also avoids presenting results in ways that identify or harm individuals or households. Because the unit of analysis is the local government unit, all interpretations are made at the area level and do not infer individual-level income behavior.

Results and Discussion

Spatial Distribution of Income Proxy, Education, and Infrastructure

The descriptive results show that the local government unit-level income proxy was spatially uneven across Samar Province. Higher scores were concentrated in city and service-linked local government units, especially Calbayog City and Catbalogan City. In comparison, lower scores appeared more frequently among rural, island, interior, and peripheral municipalities. This pattern is consistent with Philippine spatial-inequality evidence showing that economic activity and income conditions are geographically uneven rather than uniformly distributed (Pagaduan, 2023). Figure 1 shows the income-proxy surface, which serves as the study's outcome map.

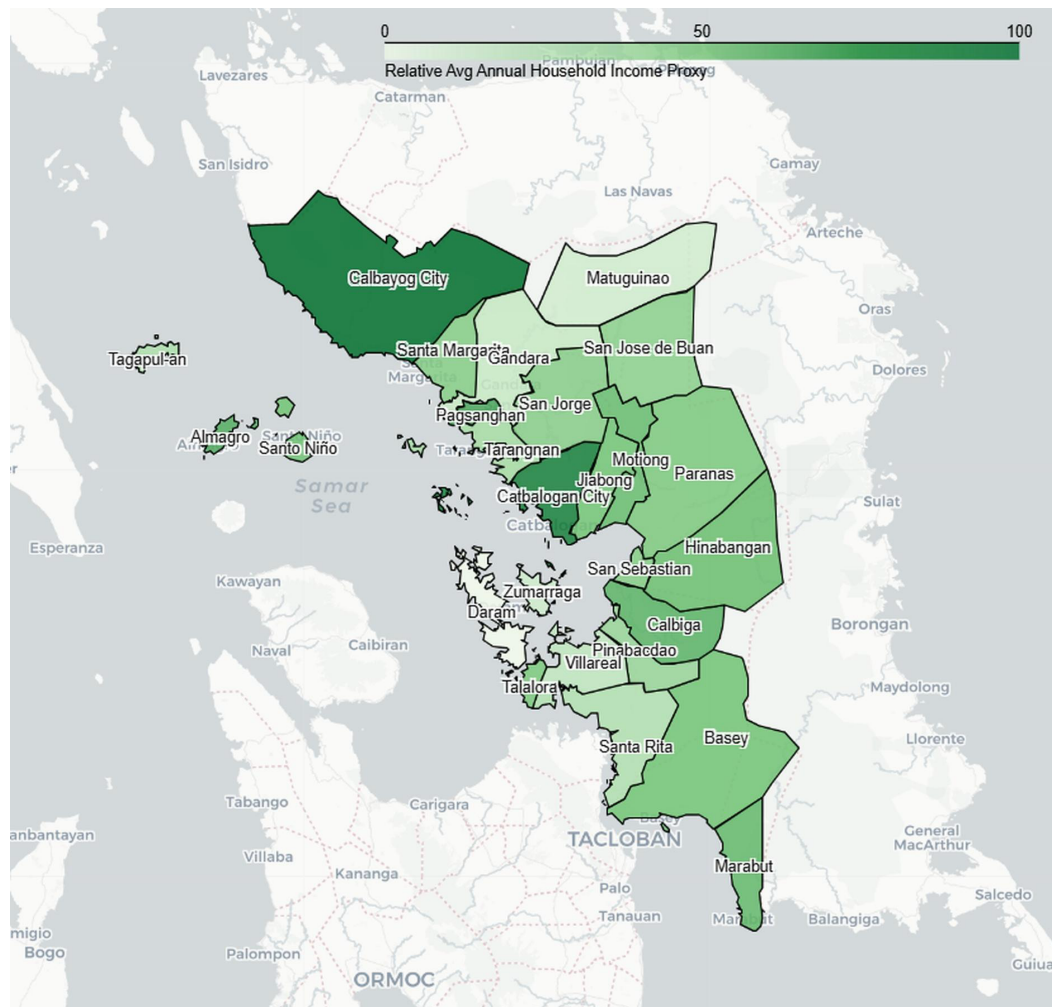


Figure 1. Spatial Distribution of Local Government Unit-Level Relative Household-Income Proxy in Samar Province

Educational attainment showed a related but not identical spatial pattern. Local government units with stronger tertiary and secondary education profiles generally occupied more favorable positions in the income-proxy

ranking. This finding supports human-capital and Philippine inequality literature indicating that education operates as an important mechanism through which localities improve income capacity and labor-market participation (Chua et al., 2015; Akita et al., 2024; Ramirez Yee, 2024). Figure 2 presents the spatial distribution of the Educational Attainment Index.

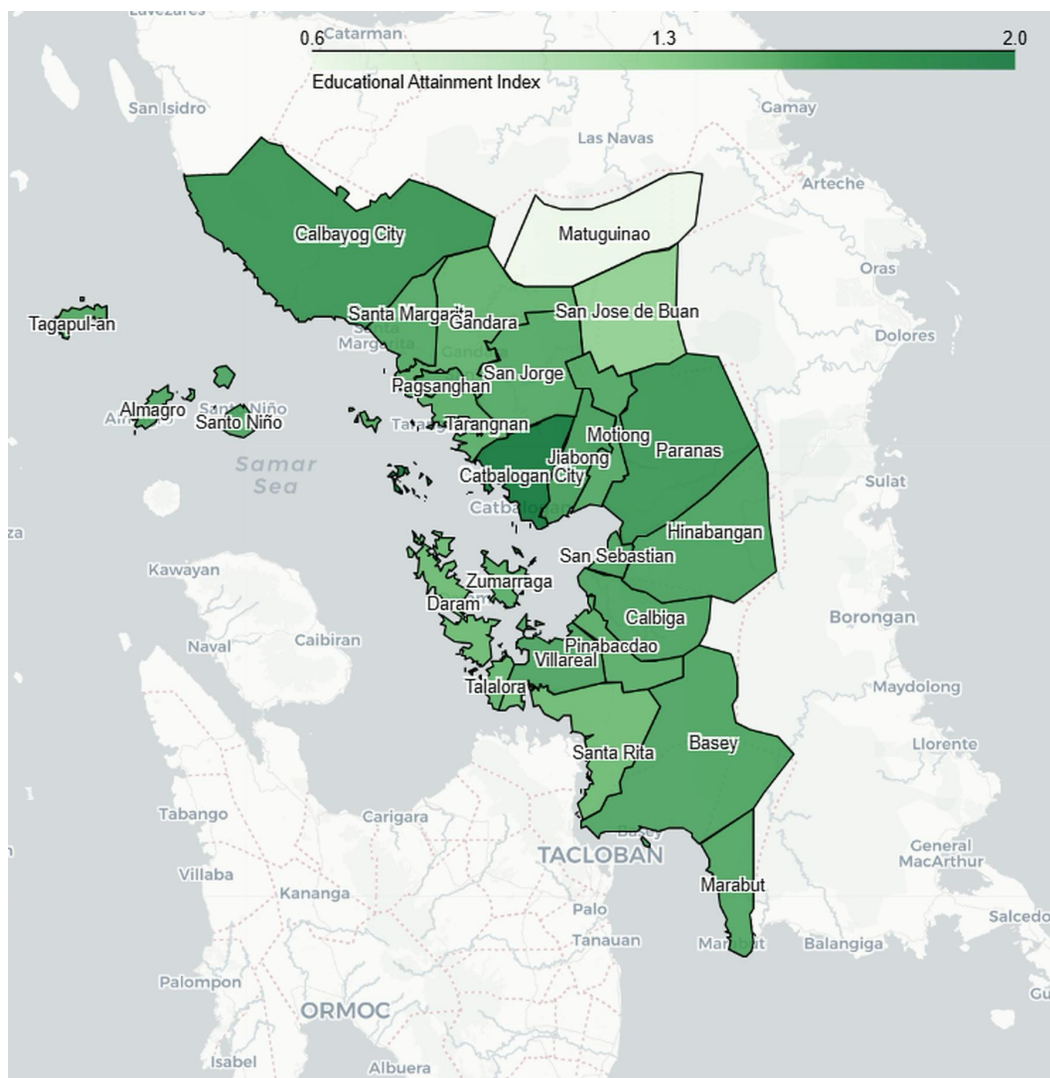


Figure 2. *Spatial Distribution of Educational Attainment Index in Samar Province*

Infrastructure access was retained as a secondary explanatory variable because infrastructure conditions are uneven across Samar local government units, although the pattern does not perfectly follow urban classification. Figure 3 is therefore useful not as the central finding, but as a comparative spatial layer. This is consistent with accessibility studies showing that infrastructure effects depend on whether facilities and networks are functionally linked to services, employment, and market participation (Medeiros et al., 2022; Guo et al., 2024; Leyso & Umezaki, 2024).

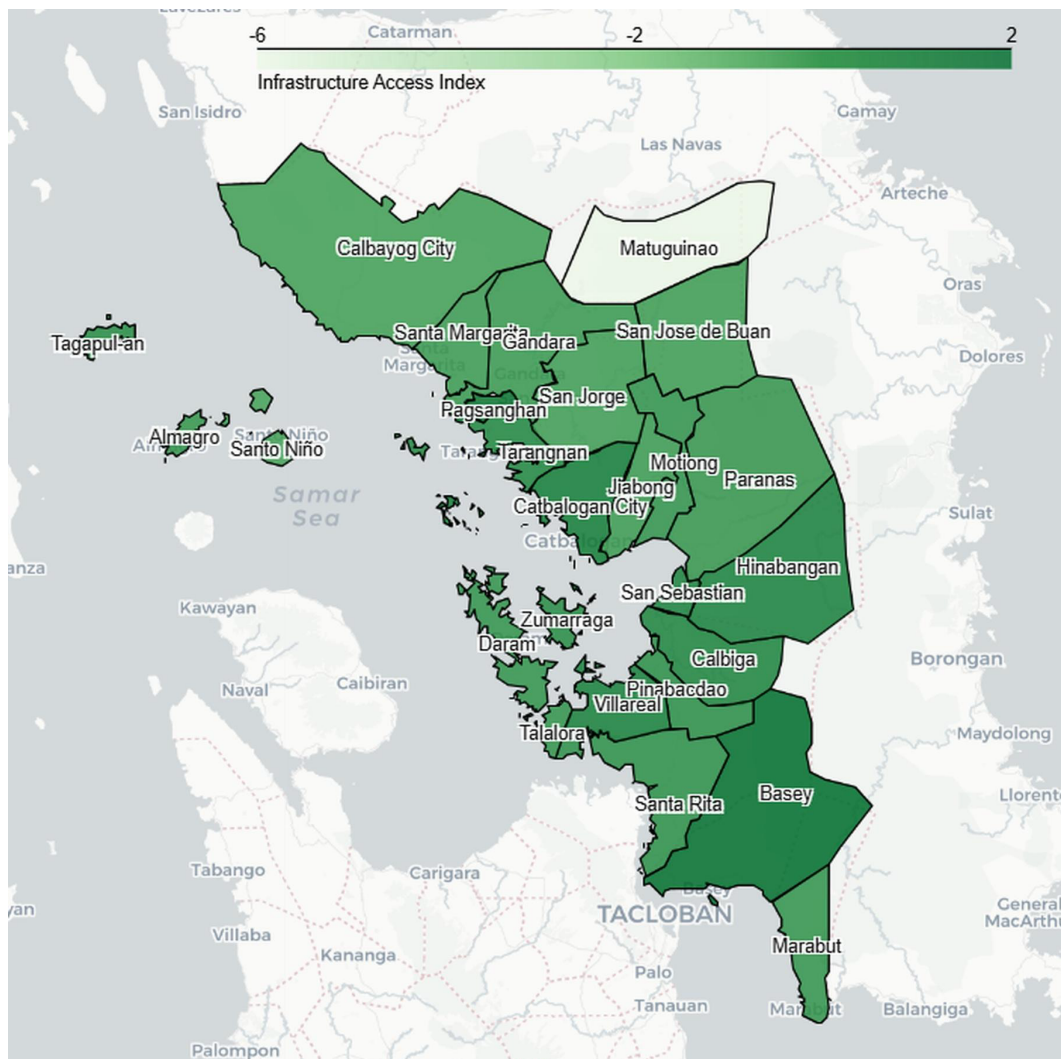


Figure 3. *Spatial Distribution of Infrastructure Access Index in Samar Province*

Interpret the maps as descriptive spatial evidence rather than formal tests of spatial autocorrelation. Although the mapped patterns suggest visible territorial unevenness between city, service-linked, interior, island, and peripheral local government units, the study did not compute Moran's I, Local Indicators of Spatial Association, or Gini-based inequality indices. Therefore, the manuscript does not claim statistically confirmed spatial clustering. Instead, the maps function as visual evidence to identify spatial differentiation and guide interpretation of the correlation and regression results. Future research may extend this analysis by applying formal spatial-dependence and inequality measures.

Association between Education and Income Proxy

Pearson correlation analysis showed a strong and statistically significant association between educational attainment and the local government unit-level income proxy ($N = 26$), $r = .64$, $p < .001$. This means that local government units with higher Educational Attainment Index scores tended to have higher relative income-proxy scores. The relationship does not establish causality, but it provides evidence that education is a strong marker of local income capacity at the local government unit scale. This result is aligned with Philippine studies showing that education and skill endowments help explain urban-rural income and wage differences (Chua et al., 2015; Zamora & Dorado, 2015).

The education result supports the human-capital expectation that areas with stronger educational profiles tend to show stronger income capacity. However, the finding should not be read as a simple causal claim that schooling automatically produces income. Because the unit of analysis is the local government unit, the result indicates that education functions as a territorial capacity. Its income relevance depends on whether local economies can absorb

educated workers, whether residents can access employment centers, and whether skills match available livelihood and labor-market opportunities.

Because the unit of analysis is the local government unit, interpret the results at the area level rather than at the household or individual level. The association between educational attainment and the income proxy does not mean that every educated resident earns more income. Rather, it indicates that local government units with stronger educational profiles tend to occupy stronger relative income-capacity positions. This ecological design may obscure intra-municipal disparities, particularly in large local government units where urban centers, coastal barangays, upland communities, and island settlements may experience different levels of access, livelihood opportunity, and income condition.

Table 2. *Pearson Correlations Among the Income Proxy and Core Explanatory Variables*

Variable 1	Variable 2	Pearson <i>r</i>	<i>p</i> -value	Interpretation
Income proxy	Urban-rural classification	.53	.005	Significant
Income proxy	Educational Attainment Index	.64	< .001	Significant
Income proxy	Infrastructure Access Index	.29	.151	Not significant
Urban-rural classification	Educational Attainment Index	.55	.004	Significant
Urban-rural classification	Infrastructure Access Index	.21	.304	Not significant
Educational Attainment Index	Infrastructure Access Index	.15	.462	Not significant

The correlation pattern narrows the policy explanation of urban-rural disparity. If income differences were explained only by settlement classification, the policy response would be limited to location-based investment. Instead, the results suggest that human capital is a major channel through which place-based advantage is converted into income capacity. This does not negate geography; it clarifies that geography becomes developmentally meaningful partly through the human-capital resources available within each local government unit.

Hierarchical Regression Results

The hierarchical blockwise regression clarified the relative contribution of geography, education, and infrastructure. Model 1 showed that geographic location alone explained 28.12% of the variance in the income proxy ($R^2 = 0.28$, $F(1, 24) = 9.39$, $p = .005$). Adding the Educational Attainment Index in Model 2 increased explained variance to $R^2 = 0.45$, $\Delta R^2 = 0.17$, $\Delta F(1, 23) = 7.14$, $p = .014$, indicating that education contributed meaningful explanatory power beyond location. Model 3 added the Infrastructure Access Index, but the increase in explained variance was minimal, $\Delta R^2 = 0.00$, $\Delta F(1, 22) = 0.02$, $p = .893$. In the final model, education remained the strongest statistically defensible predictor, while infrastructure did not contribute a distinct net effect after accounting for geography and education.

Table 3. *Hierarchical Blockwise Regression Model Summary for the Local Government Unit-Level Income Proxy*

Model	Predictors entered	R^2	Adjusted R^2	ΔR^2	<i>F</i> / <i>F</i> -change	Standardized β
Model 1	Geographic location only	0.28	0.25	0.28	$F(1, 24) = 9.39$; $p = .005$	Location $\beta = .53$
Model 2	Geographic location + Educational Attainment Index	0.45	0.40	0.17	$\Delta F(1, 23) = 7.14$; $p = .014$	Location $\beta = .26$; Education $\beta = .50$
Model 3	Geographic location + Educational Attainment Index + Infrastructure Access Index	0.45	0.38	0.00	$\Delta F(1, 22) = 0.02$; $p = .893$	Location $\beta = .22$; Education $\beta = .49$; Infrastructure $\beta = .17$

The non-significant infrastructure result is theoretically important rather than merely statistically weak. It suggests that infrastructure access, when measured at the local government unit level, may not operate independently from human capital and geographic location. Infrastructure may be necessary for development but insufficient for reducing income disparity if it is not accompanied by skills formation, institutional support, market linkage, and productive livelihood systems. This finding responds to infrastructure literature that cautions against treating physical access as a stand-alone equalizer.

The non-significance of infrastructure may reflect both measurement and structural explanations. Methodologically, the Infrastructure Access Index captures broad access indicators but does not fully measure functional quality, reliability, maintenance, travel time, service adequacy, internet speed, road condition, staffing, or institutional performance. Substantively, infrastructure may be necessary but insufficient for income improvement when it is weakly connected to labor markets, enterprise formation, livelihood systems, and skills utilization. In this sense, the result does not show that infrastructure is unimportant; rather, it suggests that

infrastructure may not predict income independently unless supported by human capital and institutional capacity.

These results answer the article objectives directly. First, the maps show that the income proxy, education, and infrastructure are unevenly distributed across Samar local government units. Second, education shows the strongest bivariate relationship with the income proxy. Third, regression results show that education explains additional income-proxy variation after accounting for geography, whereas infrastructure remains descriptively and policy relevant but not independently significant in the final statistical model. The finding is also consistent with infrastructure literature indicating that infrastructure is most effective when connected to productive skills, markets, and institutions rather than treated as a stand-alone equalizer (Nugraha et al., 2020; Medeiros et al., 2022).

Policy Meaning of the Education-Centered Result

The findings do not imply that infrastructure is unimportant. A non-significant infrastructure coefficient only means that, within this local government unit-level model, infrastructure access did not explain additional variance after geography and education were already considered. Infrastructure is better interpreted as an enabling condition: it becomes income-enhancing when linked to skills, livelihood systems, markets, enterprise formation, and institutional support.

The policy implication is therefore not education alone, but a synergistic strategy linking education, infrastructure, and institutional support. Education strengthens the human-capital base; infrastructure expands mobility and access to services; and governance institutions connect both to employment, enterprise development, market participation, and sector-specific livelihood systems. For Samar Province, this means aligning education and technical training with local economic functions: fisheries and coastal enterprise in coastal local government units; agriculture and agro-processing in interior municipalities; tourism and services in corridor local government units; and administrative, educational, and market services in city local government units.

This interpretation also guards against overstating education's role. The observed association between education and the income proxy should not be interpreted as a pure education effect. Other unmeasured factors may confound or mediate the relationship, including migration, remittances, informal employment, household asset ownership, sectoral composition, local governance capacity, and labor-market absorption. These factors may allow some local government units to show stronger income-proxy values even when local employment opportunities remain limited.

Conclusion

The study contributes local government unit-level evidence that educational attainment is the strongest observed statistical factor associated with relative household-income capacity in Samar Province. However, it should be understood as part of a broader spatial development system. Human capital matters because it may improve employability, public-sector access, enterprise participation, skilled migration, and residents' and localities' ability to convert services and infrastructure into productive opportunities.

The contribution is therefore not the claim that education alone reduces urban-rural income disparity. Rather, the study shows that human capital can function as a spatial development asset when linked to infrastructure functionality, institutional support, and labor-market absorptive capacity. For provincial planning, this means that income-disparity interventions should combine education and technical-vocational alignment with transport and digital access, market linkage, enterprise support, and locally specific livelihood strategies.

The conclusion must be read in light of the study's design limitations. The analysis is cross-sectional, ecological, and based on proxy measures; therefore, it cannot establish causality, household-level income behavior, or changes over time. The income proxy is a relative local government unit-level measure, not an official estimate of household income in pesos. Potential confounders such as migration, remittances, informal economies, household assets, sectoral employment structure, governance capacity, and labor-market absorption were not directly measured. The small number of local government units also limits the stability of regression estimates even though the data represent a complete provincial enumeration.

Future research may improve the analysis by using household-level income data, longitudinal local government unit data, more refined infrastructure-quality indicators, and formal spatial-dependence or inequality measures

such as Moran's I, Local Indicators of Spatial Association, or Gini coefficients. Additional studies may also test whether technical-vocational education, tertiary completion, school quality, migration, or labor-market absorption explains income differences more precisely than a general Educational Attainment Index.

Contributions of Authors

Jessabel C. Orongan: conceptualization, methodology, data curation, formal analysis, visualization, writing-original draft, and writing-review and editing.

Funding

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

Conflict of Interests

The author declares no conflict of interest.

Acknowledgment

The author acknowledges the Philippine Statistics Authority and the National Mapping and Resource Information Authority for the official data sources used in this study; the adviser, reviewers, and editorial evaluators for their scholarly guidance and constructive comments that improved the manuscript; and the author's partner for non-technical support during the completion of the manuscript.

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