Enhancing Poverty Estimation for Satellite Data using Deep Learning

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ABSTRACT
Understanding the level of poverty in various locations is important for the betterment of livelihoods and helps governments and organizations plan for development. Traditional approaches and data sources, such as DHS, are indeed informative but very often complex, expensive, and limited to smaller geographies. In overcoming such limitations, this research uses satellite imagery combined with deep learning, developing a system to leverage these data sources into better outcomes in the estimation of poverty on a larger scale. The system predicts local poverty by using daytime multispectral images, nighttime lights, and ground truth survey data. The estimated absolute poverty estimation framework includes a two-phase approach: Nighttime images were used in the first phase, through a deep learning model using the SatMAE architecture, which classified rural and urban areas using daytime satellite images. Nighttime images were gathered along with daytime images to avoid temporal data constraints. The nighttime model classifies rural and urban areas. During daytime images, the indicators NDVI, NDBI, and NDWI combined predictive features to estimate a poverty score. The model estimating external uncertainty joins the absolute poverty estimation framework in order to assess the confidence level of any given prediction. This model ensures that it can scale poverty estimation, that it is reliable, and that it will help policymakers in resource allocation in areas identified and believed to be underdeveloped.

General Terms
Satellite imagery, Deep learning, Explainable AI, Uncertainty quantification, Multispectral data, Nighttime light data, SatMAE, Remote sensing, Socioeconomic analysis.

Keywords
Poverty Estimation, SatMAE, Multispectral Satellite Imagery, Nighttime Light Data, NDVI, NDBI, NDWI, Urban–Rural Classification, Uncertainty Quantification, Explainable AI.

1. INTRODUCTION
Poverty is perhaps one of the most enduring and deep-rooted issues in the world and impinges not only on economic growth, but also on education, health, and the overall well-being of society. All policymakers, governments, and development agencies need accurate and current measures of poverty in order to deal with the problem effectively, such as channelling resources and designing focused interventions. Conventionally, poverty measures originate from surveys at the household level, e.g., the Demographic and Health Surveys (DHS) or Living Standards Measurement Study (LSMS). These are costly to carry out, require a lot of time to apply, and have geography bias due to fewer surveys available in the poor and rural nations, resulting in data that will be incomplete or keep on growing old by the day. With the advancements in deep learning, newer Earth Observation (EO) basis models like SatMAE, which are capable of enabling the direct extraction of high-level spatial and spectral features from satellite images, have also evolved. Yet, although predictive accuracy has been enhanced, the biggest shortcoming with most models is that there is no uncertainty estimation knowing the extent to which model-driven predictions are reliable. Uncertainty is absolutely essential in a decision process, were inaccurate, or overconfident, predictions might result in mistakenly allocating yellow resources. In light of this, this study proposes the development of an accurate poverty estimation system based on deep learning that is trustworthy and interpretable, while integrating diverse data sources including daytime and nighttime satellite imagery along with survey-derived ground truth data. Conventional methods of estimating poverty rely on socioeconomic surveys that are conducted every few years and geospatially limited. This results in spatio-temporal gaps in information, therefore not enabling real-time monitoring of poverty change, and adds or exacerbates challenges in conducting socio-economic surveys in developing or remote locations through cost and logistics. Prior approaches to machine and deep learning methods that rely on satellite imagery have improved on predicting proxy measures of poverty such as wealth indices, or consumption, all of which are typically image feature only based approaches without including domain knowledge information like urban-rural characteristics, or environmental indices. They only offer point estimates of poverty without estimates of certainty or uncertainty. Thus, the guiding research question is to develop and mobilize a deep learning-based model to predict poverty and poverty ranks from satellite imagery and survey data, whilst giving estimates of predictive uncertainty, thus facilitating actionable and defensible study results. This study thus aims to build a framework that consumes multi-source satellite imagery and ground-truth survey data, adopted a SatMAE network to extract features, and employs an external uncertainty model to improve the confidence of estimates and aid the interpretability of poverty estimates.

2. OBJECTIVES
The goal of this study is to develop a system based on deep learning to predict poverty regionally from satellite imagery and survey data. The specific objectives are:

Integrate Multi-Source Data: fuse daytime multispectral satellite data, nighttime light data, and DHS ground-truth survey data together to a cohesive understanding of the socioeconomic construct of the region.

Urban–Rural Categorization: categorize regions as urban or rural based on daytime and nighttime imagery and utilizing a pretrained model SatMAE, so the system can use contextual driven feature weighting to make accurate predictions.

Compute Environmental Indices: to compute NDVI, NDBI, and NDWI from daytime imagery to capture vegetation, built-up density, and water availability, which are important environmental indicators that co-relate with poverty.

Poverty Estimation using SatMAE: deploy a regression model that was tuned within SatMAE (during training) on daytime imagery and indices to predict the mean poverty level (μ) over regions.

Uncertainty Estimation: make use of an external uncertainty model (MLP/CNN) that estimates prediction confidence to generate good quality, explainable poverty estimation data and results.

3. LITERATURE REVIEW

The use of satellite imagery and deep learning approaches to estimate poverty has been an evolving point of interest in the domains of geospatial analytics and remote sensing. Over the last decade, the research has advanced from investigating simple relationships of correlating light intensity and income to developing complex models that integrate large volumes of nighttime light intensity, vegetation indices and socioeconomic indicators. The studies reviewed are all aimed at addressing the key challenges associated with poverty mapping spatial heterogeneity, lack of ground truth, and model uncertainties by leveraging the capabilities of machine learning and deep learning for accurate, interpretable, and robust poverty maps.

3.1 Nighttime Light–Based Poverty Estimation

Nighttime light (NTL) data, captured by sensors such as VIIRS and DMSP-OLS, have been used for estimating economic and poverty level. Many Researches have correlated light intensity with income levels, infrastructure, and development indicators. In recent years, NTL data generated by sensors like VIIRS and DMSP-OLS have become the primary indicators for poverty and economic activity detection. Researchers have demonstrated that light intensity correlates positively with income, infrastructure, and development. Among the different researches on nightlight intensity, those conducted by Yu et al. [2] and Islam et al. [1] are the ones that laid the groundwork for this field. The two works used VIIRS VNP46A3 provided by NASA and found light intensity to be very closely related to the national GDP and income levels, thus paving the way for large-scale economic mapping to be done with a pretty accurate, cost-effective, and non-invasive option. Then, Wu, and Tan [3], besides others, have pointed out, on the one hand, that although economic models reveal macro-level trends, they still do not reflect rural poverty, given that the night-time light data saturation or becomes uninformative for cities and highly illuminated urban areas. However, rural areas might have low levels of night-time light due to less electrification even though they are economically active. Therefore, while this proxy possesses some value for poverty assessment at the macro level, it still lacks precision at the microscale which leads to the non-capturing of the heterogeneity of poverty across social and infrastructural conditions.

Table 1. Summary of nighttime light-based poverty estimation studies

Study	Approach / Architecture	Key Features	Outcomes & Limitations
M. S. Islam et al. [1]	Deep learning on NASA VIIRS (VNP46A3 / VNP46A4) data	Lunar correction, denoising, socioeconomic correlation analysis	Improved illumination- bias handling; limited to a single region
B. Yu et al. [2]	Integrated Poverty Index (IPI) using NPP–VIIRS	Correlation of nighttime lights with county-level poverty in China	Effective macro-level results; lacks micro-spatial accuracy
P. Wu and Y. Tan [3]	ResNet50 - based economic indicator estimation using remote sensing imagery	Transfer learning from remote sensing to socio-economic indicators	Good cross-region feature transfer; limited temporal adaptability

3.2 Multispectral and Daytime Imagery–Based Approaches

Daytime satellite images provide additional information such as vegetation, water bodies, and building infrastructure. Integrating these features with NTL data enhances reliability and model efficiency. Daytime satellite imaging gives additional information that is similar to the NTL data and includes vegetation, water, and building structures which are useful for interpreting and generalizing the model with NTL data. To enhance the NTL data, the scientists made use of daytime satellite imagery and spectral indices (e.g., NDVI, which was explored in this study) to achieve a better grasp of the model predictions. Ni et al. [4] were the pioneers using together daytime and nighttime satellite data and they reported a significant increase in prediction accuracy due to the environmental illumination features being captured. Notably, Banerji et al. [6] and Gupta et al. [7] have both indicated that the vegetation density and built-up indices demonstrated a strong relationship with poverty, especially as a distinguishing factor between urban and rural areas. Likewise, Arif et al. [5] found that CNNs were able to detect patterns at localized spatial levels which were significant for infrastructure and land use. Although the aforementioned studies provide a better contextual understanding of NTL data, their methods still demanded high precision for the matching process with the ground-truth socioeconomic data and the methods used were complex computing approaches.

Table 2. Summary of multispectral and imagery-based poverty estimation studies

Study	Approach / Architecture	Key Features	Outcomes & Limitations
Park et al. [20]	DNN-based classification for speech, audio, and music integration	Combined CNNs for spectral features and RNNs for temporal context	Improved metadata tagging; lacks multimodal fusion
A. Arif et al. [5]	CNN on high-resolution images (Indonesia)	Feature extraction for regional poverty estimation	Efficient and scalable; effective for local analysis; limited scalability
N. Banerji et al. [6]	CNN + NDVI, NDBI indices	Vegetation and infrastructure-based poverty mapping	Enhanced interpretability; region-specific calibration required

3.3 Hybrid Deep Learning and Foundation Models

With the emergence of large-scale self-supervised models, foundation architectures like SatMAE and ConvLSTM have shown remarkable improvements in learning spatial and temporal dependencies. The emergence of large self-supervised models has opened new ways for huge foundation architectures like SatMAE and ConvLSTM to learn spatial and temporal dependencies in an exceptionally effective manner. The recent trends in research have been directing toward mixed architectures capable of feature extraction at different levels and simultaneous learning of spatiotemporal characteristics. Tang et al. [9] invented a model based on ConvLSTM that made use of both spatial and temporal properties in poverty estimation, thereby bridging the gaps of cross-temporal consistency. Jarry et al.[10] pitted spatial and spatio-temporal paradigms against one another and declared time- conscious models as the more resilient ones with respect to changing economic environments. Subsequently, Kakooei and Daoud [8] came up with a SatMAE foundation model that was aware of the uncertainties and made use of the feature extraction of masked autoencoders along with the external uncertainty quantification to boost the reliability of predictions. Rotich and Sarkar [11] were a step ahead in this vein and delved into the transfer learning prospects of SatMAE and also exhibited its robustness over various datasets. All these models together have offered huge benefits not only in terms of scalabilities but also of accuracies at the cost of very high computational power and fine-tuning.

Table 3. Summary of hybrid deep learning and foundation model

Study	Approach / Architecture	Key Features	Outcomes & Limitations
M. Kakooei and A. Daoud [8]	SatMAE+ Uncertainty Quantification	Foundation model + uncertainty-aware training	Confidence estimation improves trustworthiness
J. Tang et al. [9]	ConvLSTM model	Spatio-temporal learning using multisource data	Captures evolving poverty trends; computation-ally intensive
R. Jarry et al. [10]	Spatio-temporal paradigms	Comparison between spatial and temporal modeling	Time-series integration improves resilience
G. Rotich and S. Sarkar [11]	SatMAE foundation model evaluation	Assesses robustness of large models on remote sensing tasks	Demonstrates superior transfer learning; resource-heavy

3.4 Uncertainty and Socioeconomic Correlation Frameworks

Recent studies have concentrated on integrating uncer- tainty estimation, explainability, and Socioeconomic correla- tion, therefore, enhances policy relevance.

3.5 Subsequent Pages

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Table 4. Summary of uncertainty and socioeconomic correlation frameworks

Study	Approach / Architecture	Key Features	Outcomes & Limitations
R. Ghosh et al. [12]	Computer Vision + Text Data	Integrates census data with image features	Improved explainabilit; complex data preprocessing
S. Ballem et al. [13]	ML with multiple open-source datasets	Combines OSM, Landsat, and DHS data	Good transferabilit; limited model interpretability
H. Zhang et al. [14]	Faster R-CNN	Object-level detection of poverty indicators	Detects urban patterns; high compute cost
M. Oh et al. [15]	Photovoltaic estimation for humanitarian poverty proxy	Satellite-based energy accessibility estimation	Humanitarian relevance; indirect poverty link

The literature reviewed portrays a scenario of steady development in poverty estimation. methodologies-from traditional light-based regressions to state-of-the-art deep learning and foundation model architectures. Modern frameworks such as ConvLSTM and SatMAE enables both spatial and temporal feature learning, while emerging uncertainty Quantification modules improve prediction confidence. Notwithstanding these advances, challenges remain in crosscountry generalization, dataset imbalance, model interpretability, and large-scale computational cost. The proposed Work in this report builds on these insights, introducing a hybrid SatMAE-based deep model with integrated urban–rural feature prioritization and uncertainty Quantification will aim to deliver reliable, scalable, and interpretable poverty mapping.

4. METHODOLOGY OVERVIEW

The proposed model utilizes multisource satellite data in addition to deep learning techniques to estimate poverty levels across different areas. A framework that combines daytime and nighttime satellite images with ground-truth data from the DHS is proposed. It follows a two-phase SatMAE-based model, for classification and then for regression, followed by an uncertainty estimation model that offers both predictions and confidence levels.

1. Data Collection: Data is taken from multiple sources: Daytime images from Landsat 8/9 or Sentinel-2, Nighttime Light data from VIIRS or DMSP-OLS, and ground-truth DHS data containing Wealth Index and urban/rural labels. DHS coordinates are used to match images with survey data.

2. Spatial Alignment and Patch Extraction: All datasets are aligned to the WGS84 coordinate system. Fixed-size patches (e.g., 224×224 pixels) centered on each DHS cluster are extracted to form paired image survey samples.

3. Data Preprocessing: Normalization is used to convert pixel values of every spectral band to a scale of 0 to 1. Cloud masking uses the relevant quality masks to eliminate the pixels that are covered by clouds. Resampling resamples to a consistent resolution across all images (for instance, 30m/pixel).

4. Environmental Index Calculation: Three indices are computed to capture land-cover features:

$$NDVI = (NIR - Red) / (NIR + Red) \quad (1)$$

$$NDBI = (SWIR - NIR) / (SWIR + NIR) \quad (2)$$

$$NDWI = (Green - NIR) / (Green + NIR) \quad (3)$$

These indices serve as numerical features linked to each image patch.

5. Urban–Rural Classification: Nighttime patches are processed using a pretrained SatMAE decoder. A softmax classifier determines urban or rural category:

$$P(Urban) = Softmax(W \cdot f\_NL) \quad (4)$$

where f_NL represents SatMAE features extracted from nighttime images.

6. Feature Fusion and Conditional Weighting: The fused features include daytime embeddings (fDay), environmental indices, spatial features, and the urban/rural label. A weighted combination is applied:

$$f\_final=w\_c \odot f\_Day+(1-w\_c) \odot f\_env \quad (5)$$

where w_c adjusts weights according to urban–rural characteristics.

7. Poverty Prediction Model: A regression model predicts the mean poverty score (μ) using Mean Squared Error (MSE) loss:

$$MSE = (1/N) * \Sigma (y_{true} - y_{pred})^2 \quad (6)$$

where y_{true} is the DHS Wealth Index and y_{pred} is the model output.

8. External Uncertainty Estimation: The mean poverty prediction (μ) and SatMAE embeddings are fed into an external model: MLP/CNN to predict uncertainty, (σ):

$$NLL=(1/2)\Sigma_{i=1}^{N}[\log(\sigma_i^2)+((y\_true,i-\mu\_i)^2/\sigma\_i^2)] \quad (7)$$

This Negative Log Likelihood loss penalizes both inaccurate and overconfident predictions.

9. Evaluation Metrics: Model performance is evaluated using regression metrics ($R2$, RMSE, MAE) and uncertainty metrics (NLL, coverage within ±1σ and ±2σ) to evaluate prediction accuracy and calibration.

10. Visualization and Output Generation: Two maps are generated: a Poverty Map (μ) showing predicted average poverty and an Uncertainty Map (σ) showing model confidence. Final predictions are expressed as:

$$F\_finalOutput = \mu \pm \sigma \quad (8)$$

11. Deployment and Decision Support: Outputs are visualized in GIS dashboards for policymakers. Areas with high uncertainty (σ) are prioritized for additional data collection, enabling data driven monitoring and better resource allocation.

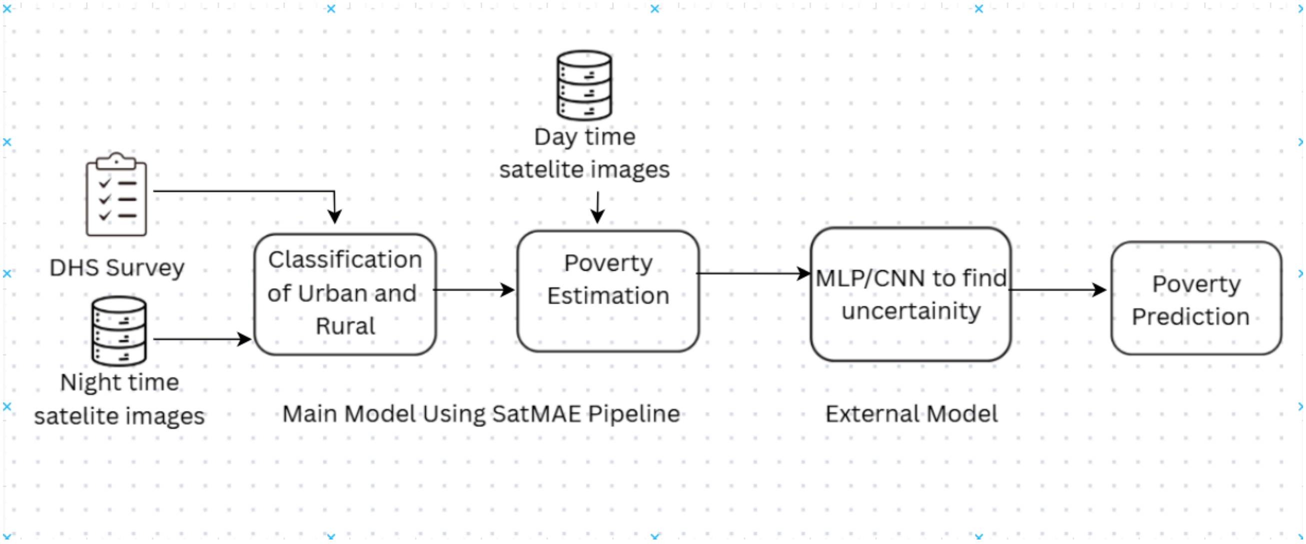

Fig 1: Poverty estimation architecture

5. ANALYTICAL DISCUSSION

The proposed framework is analytically grounded in the need for scalable and data-driven poverty estimation. Traditional survey-based approaches are temporally infrequent and geographically limited, restricting their applicability for real-time policy interventions. By leveraging satellite imagery, the system enables broader spatial coverage and consistent monitoring. This shift from survey dependency to remote sensing–based inference provides a structurally scalable alternative for socio-economic assessment. The selection of SatMAE as the core architecture is theoretically justified by its ability to learn contextual spatial representations through masked autoencoding. Unlike conventional convolutional neural networks that primarily capture localized features, transformer-based models can model long-range spatial dependencies. Such capability is particularly important in poverty estimation, where economic conditions are influenced by broader settlement patterns, infrastructure distribution, and environmental characteristics rather than isolated pixel-level features. The integration of daytime imagery with nighttime light (NTL) data further strengthens the analytical foundation of the framework. While NTL intensity correlates with economic activity, it may suffer from saturation in dense urban areas and weak signals in rural regions. Daytime imagery compensates for these limitations by capturing structural and environmental features such as vegetation cover, water bodies, and built infrastructure. The complementary fusion of these modalities enhances representation diversity and improves generalization across heterogeneous geographic regions. The incorporation of an uncertainty estimation module addresses the inherent ambiguity present in satellite-based poverty prediction. Factors such as atmospheric noise, spatial displacement of survey coordinates, and sensor resolution differences introduce prediction variability. By modeling predictive uncertainty, the system provides confidence-aware outputs rather than deterministic estimates. This enhances reliability and supports risk-sensitive decision-making in policy applications.

6. MODEL DESCRIPTION

Main Model (SatMAE-based Poverty Predictor): The main model uses SatMAE, which is a Vision Transformer (ViT) tailored for multispectral satellite images and detects hidden features plus learns representations through the process of masked autoencoding which involves replacing absent patches in the image during pretraining. This allows the model to comprehend the overall spatial arrangement and the spectral difference across regions without the need for direct training on the data. A two-headed methodology is utilized once the primary model feature embeddings are extracted: Urban/Rural Classifier determines the nature of the area, Poverty Estimator assigns a relative poverty score (regression) as an estimate. The final poverty score is obtained through the integration of features from different sources: daytime imagery, nighttime lights, and human factors as represented by the Demographic and Health Survey (DHS).

External Model (Uncertainty Estimator): In the subsequent step, the external model receives the hidden features and the predictions made in phase 1 as input. The model uses a multi-layer perceptron (MLP) or shallow CNN architecture to predict the uncertainty related to the predictions through the application of various bootstrapping techniques. The external model is capable of revealing areas where the predictions are inconsistent, hence by attaching a confidence score between 0 and 1 A higher value implies greater confidence in the prediction. A lower value indicates higher predictive uncertainty, suggesting the need for additional data quality verification and further validation. This two-part system not only predicts poverty but also provides a reliability metric regarding the prediction.

7. EVALUATION STRATEGY

To ensure proper validation of the proposed system, a structured evaluation plan is defined. The dataset will be divided into training and testing sets to assess generalization performance. Cross-validation techniques will be applied to reduce bias and improve reliability of the results.

Model performance will be measured using standard regression metrics such as R^2, Mean Absolute Error (MAE), and Root Mean Square Error (RMSE). These metrics provide a balanced assessment of predictive accuracy and error magnitude. The proposed framework will be compared with baseline approaches, including models using only Nighttime Light (NTL) data and standard convolutional neural networks. This comparison will help determine the contribution of multisource imagery and transformer-based feature extraction. An ablation analysis will also be conducted by removing individual components such as daytime imagery inputs and the uncertainty module. This will evaluate the importance of each module in the overall architecture.

Finally, performance will be examined across different geographic regions, including urban and rural areas, to ensure robustness and stability. This comprehensive evaluation framework ensures methodological rigor and reliable validation of the proposed approach.

8. SCOPE AND LIMITATIONS

Scope of the Study: This study seeks to develop a poverty estimation system based on deep learning approaches combined with satellite observations and ground-truth socioeconomic survey data that offers scalable, interpretable, and data-driven poverty indicators at the regional level. It unites daytime multispectral observations, nightlights, and Demographic and Health Survey (DHS) observations to estimate the economic status of a region. SatMAE (Satellite Masked Autoencoder) model is employed as the feature extraction backbone to learn spatial and spectral patterns of the Earth's surface. The model further uses environmental indices (e.g., NDVI, NDBI, NDWI) and urban/rural categorization in an attempt to increase the quality of predictions and make the outcomes of the predictions contextualized. An external model of uncertainty is employed to estimate the level of uncertainty in each individual poverty forecast so that it will aid policymakers in determining areas where additional data collection or fact-checking operations are needed. The uncertainty model does this through the application of poverty maps and uncertainty maps that will show the forecasted poverty conditions and the credibility of the poverty forecasts. Overall, the study demonstrates the capability of deep learning and remote sensing to enable mapping of poverty experiences; and offers a more effective alternative to conventional survey instruments while enhancing sustainable development planning, and raising policy design and implementation.

Limitations of the Study: Apart from its advantages, the system being suggested has technical and data-limitations: Quality and Resolution of the Data: There exists atmospheric noise and cloud cover to influence satellite imagery even disregarding the various resolutions provided by various sensors (e.g., Landsat vs. VIIRS). These can influence the extraction of features as well as the precision of models,Ground-Truth Data Restrictions: The DHS data contains poverty data for a restricted set of regions and years. This restricts the model to training only within a narrow set, and implications of extrapolating the model to regions with no survey coverage is thus restricted, DHS data location jitter: As a design choice, DHS cluster coordinates are shifted (up to 5-10 km) for privacy, resulting in the possibility of spatial mismatches between the actual location and the satellite patch employed in the prediction, Computational Power: Tweak large pre-trained models such as SatMAE and train a model for uncertainty, which is computationally heavy and needs to be done on GPU, Interpretation: Even though the model generates poverty map visualizations and uncertainty levels, it is problematic to fully interpret causal relationships that exist between features of satellites and levels of poverty, Temporal Variability: The timing of gathering satellite images and surveys would not necessarily coincide, hence temporal inconsistency that affects prediction accuracy based on the difference in economic conditions between sources of data

9. CONCLUSION

This research explored how deep learning and Earth observation data can be integrated to enhance poverty estimation and yield sound information for policy and development planning. The experimental analysis and literature review suggest that although there has been good accuracy with conventional machine learning and deep learning models, they have tended to concentrate on prediction alone without considering uncertainty or interpretability. This restricts their utility in practical decision-making, where it is as critical to know the confidence and rationale for a prediction. To overcome such shortcomings, this research presented a Deep Learning–Based Poverty Estimation Framework with Explainable Uncertainty Modeling by combining the SatMAE foundation model with an uncertainty module external to it and Explainable AI (XAI) components. The SatMAE model successfully extracts spatial and spectral patterns from daytime and nighttime satellite imagery, while the uncertainty module gives confidence estimates with each prediction. The addition of explainability methods further increases transparency, so users can see why and how the system makes some predictions. This approach helps overcome the limitations of traditional survey-based and black box AI models by providing a degree of accuracy and confidence in poverty prediction systems. It offers a scaleable, low-cost, and interpretable system which could aid governments and organizations in identifying vulnerable regions and making policy decisions. In this regard, future studies should be focused on applying this framework to different regions, enhancing computational efficiency, and integrating more human-centered XAI methods for better interpretability. These directions will enhance the system's ability to act as an efficient tool for poverty monitoring in the world and sustainable development.

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