MAKERERE UNIVERSITY

URBAN-RURAL ENERGY DISPARITIES IN FOCUS: AN XAI APPROACH TO BIOMASS ALLOCATION STRATEGIES

Authors: Ronald Atuhaire, Tendo Christine, George Ssemaganda

Affiliations: CoCIS, Department of Computer Science, Makerere University, Uganda

Introduction

Uganda faces a critical energy challenge, with **95%** of its population relying on biomass for fuel (World Bank, 2020), driving deforestation and energy inequity.

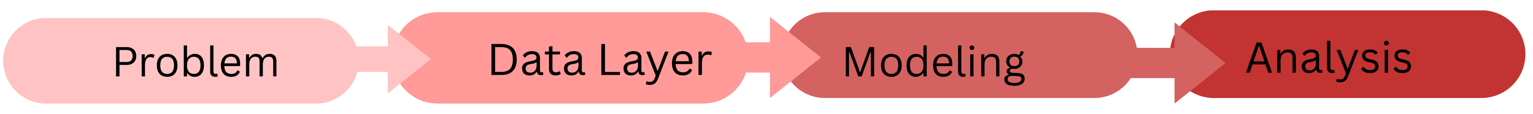
This study leverages machine learning to:

- Predict district-level energy capacity
- Identify deforestation risks
- Guide sustainable resource allocation
- Compare model efficacy in low-data settings

Methodology

Data from **56** districts was processed into five key features: *hardwood/softwood stocks, tropical forest loss metrics, and spatial coordinates.* After stratified splitting, three models were trained: *Random Forest, TabTransformer, and GAT*. XAI was achieved through SHAP (global), LIME (local), and Integrated Gradients (spatial).

Figure 1. Chronological process of implementing our research.



A scenario engine simulated 5% conservation gains. Initial analysis revealed stark disparities: energy potential ranged from 118,800 GJ to 17.7M GJ across districts. Geospatial visualization also revealed more insights in this dataset

Figure 2. Feature Correlation Matrix

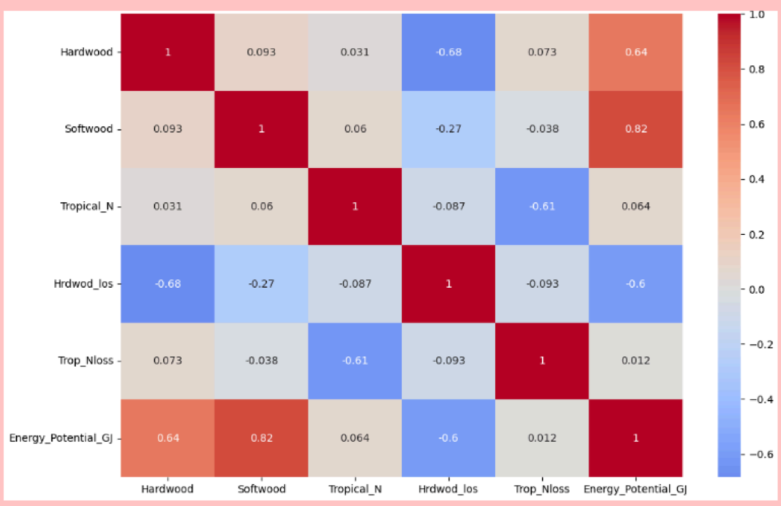
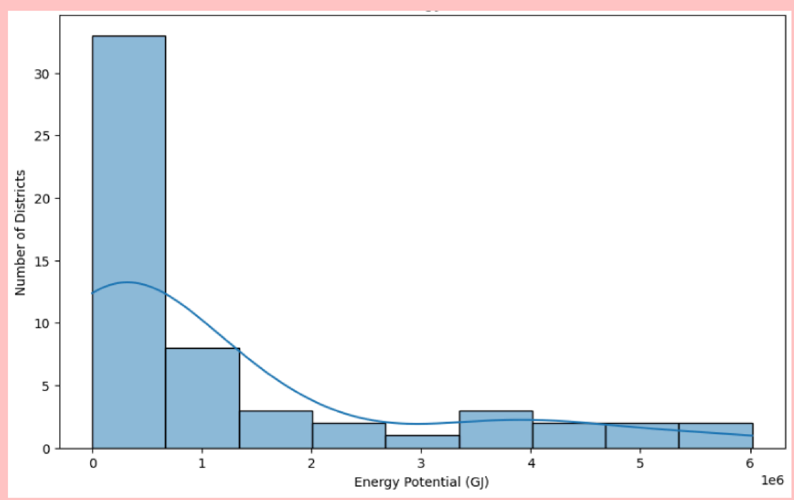


Figure 3. Uganda District-Level BE Potential

Figure 4. Biomass Energy Potential - Districts



Results & XAI (Explainable AI)

Random Forest outperformed neural models (R^2=0.89 vs. -0.39 for GAT), attributed to Uganda's small dataset (n=56). SHAP identified hardwood as the dominant predictor (42% impact), while LIME revealed nonlinear interactions between softwood stocks and urbanization.

Spatial XAI via GAT highlighted cross-district deforestation patterns, with 63% of high-loss areas adjacent to national parks. Scenario testing showed a 5% reduction in Hrdwod_los could boost energy reserves by 210,000 GJ/year in critical districts like Rakai.

Table 1. Table of results

Model	RMSE (GJ)	MAE (GJ)	R^2 Score
Random Forest	740199.55	361205.00	0.8896
TabTransformer	2930118.12	1903749.74	-0.7305
GAT	2625017.71	1713974.68	-0.3889

Figure 5. RF Feature Importances (Gini)

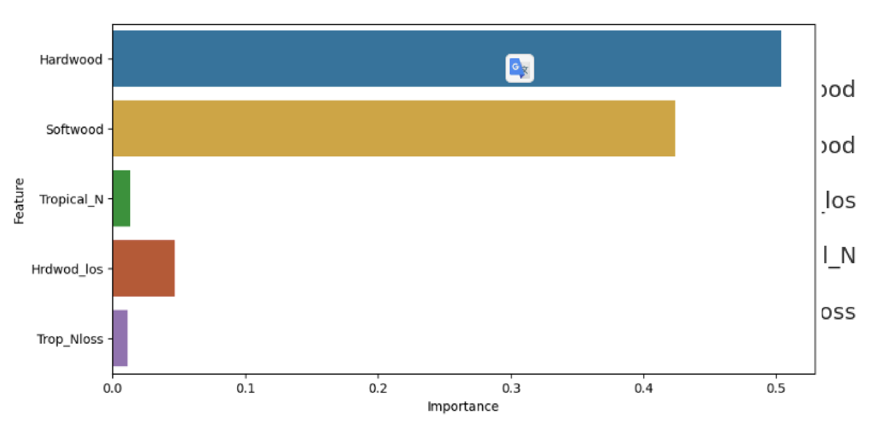


Figure 6. SHAP Plot - Model Output

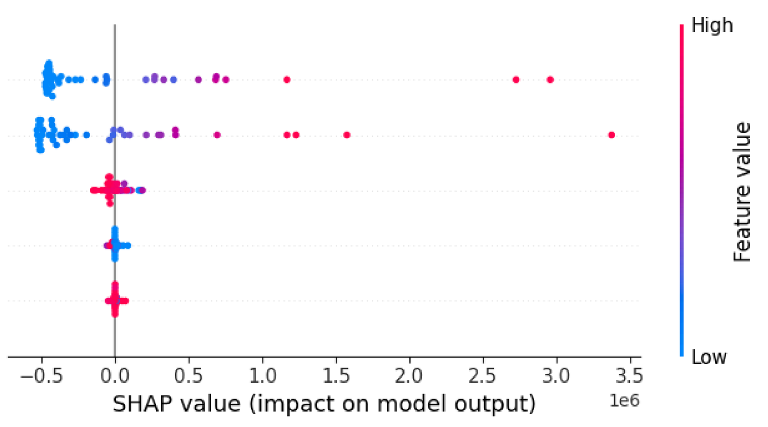


Figure 7. District-Level Energy Projections

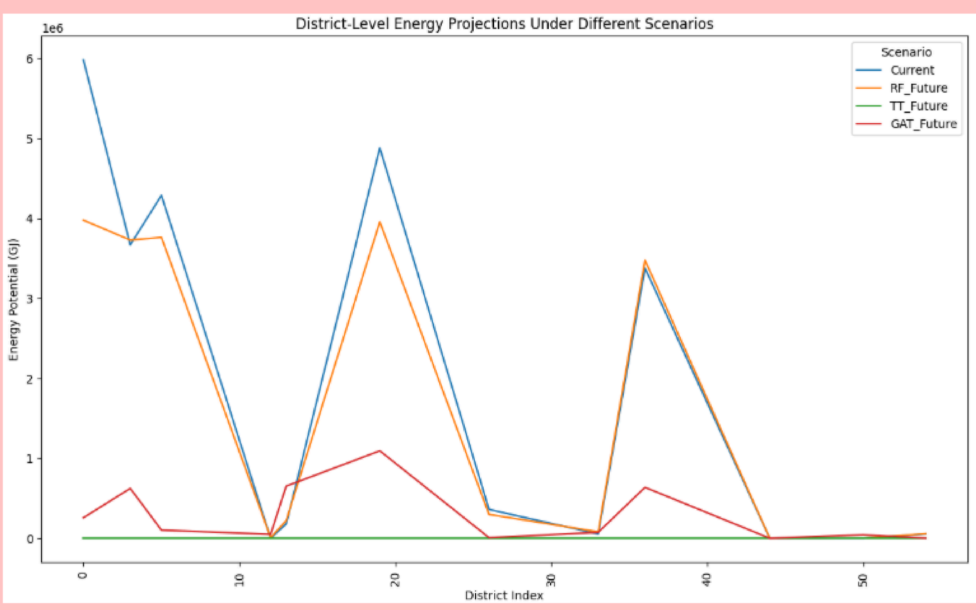


Figure 8. Top 10 Districts by BE Potential

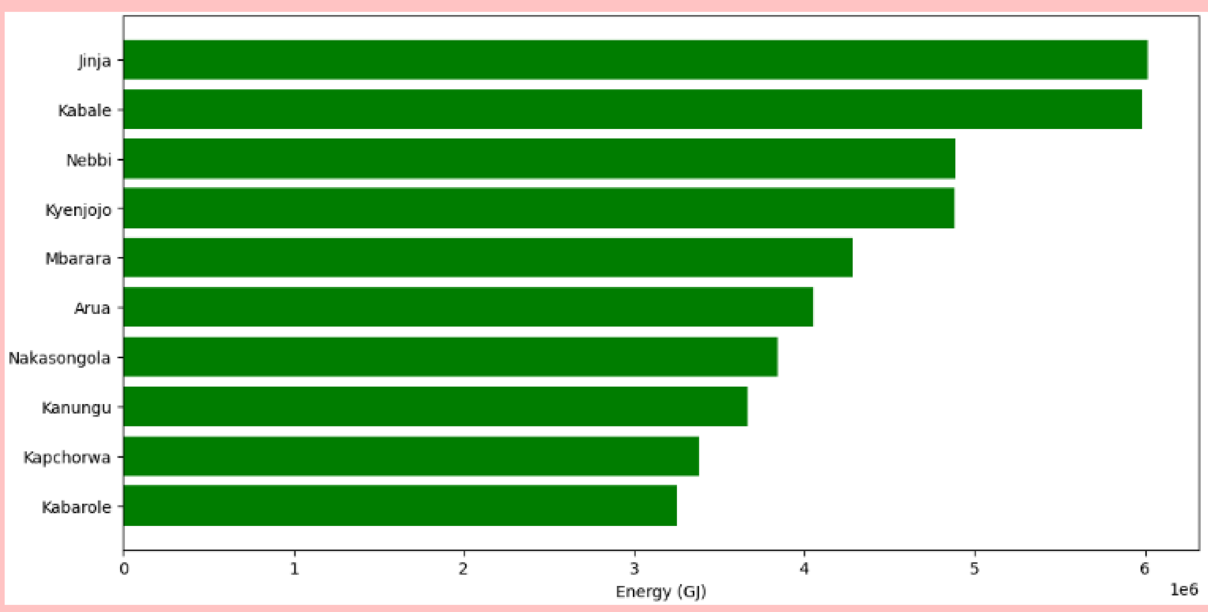
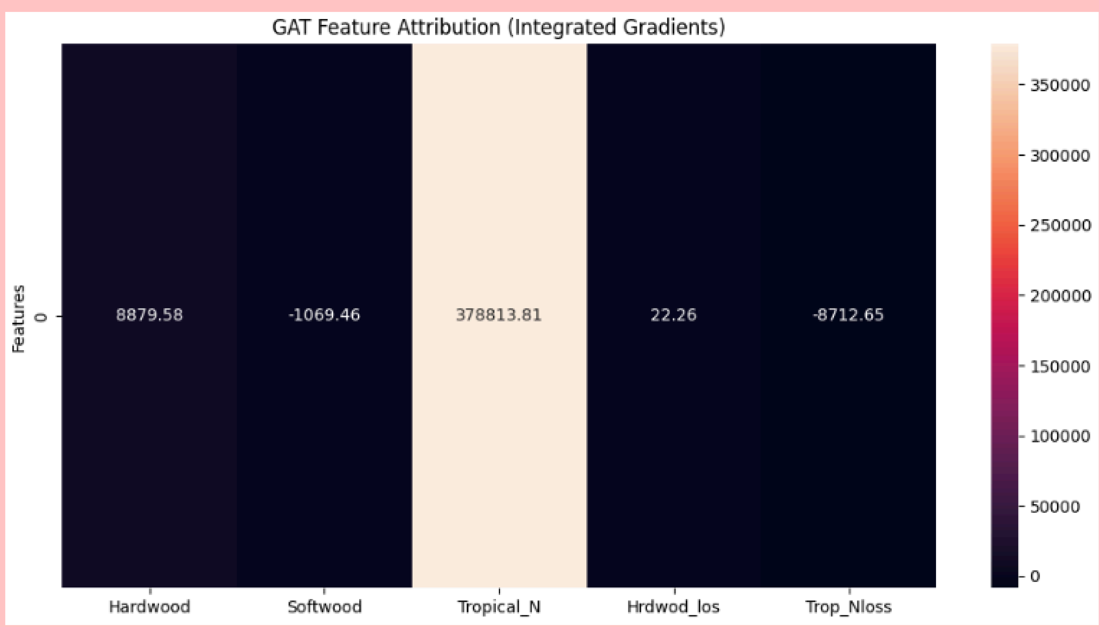


Figure 9. GAT Feature Attribution



Conclusion & Future Steps

This study demonstrates Random Forest's superiority in low-data biomass prediction while revealing neural models' potential for spatial monitoring. Three priorities emerge: *Satellite integration* to enhance spatial accuracy via Sentinel-2 NDVI data, *Hybrid modeling* combining RF's robustness with GAT's spatial awareness, and *Real-time dashboards for policymakers*, linking predictions to Uganda's Energy Policy 2023 targets.

Acknowledgements

Data Source: Ugandan Energy Sector GIS Working Group
Our Supervisor, Dr. Ggaliwango Marvin
Tools: PyTorch Geometric, SHAP, scikit-learn + Kaggle

References

1. World Bank. (2020). Uganda Energy Access Review.
2. Ribeiro, M.T., et al. (2016). "Why Should I Trust You?". ACM.
3. Velickovic, P., et al. (2018). Graph Attention Networks. ICLR.