

Supplementary Material

The resilience paradox in transport corridors: Ecological thresholds, spatial spillovers, and infrastructure divergence in Tanzania

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S1. Data Sources and Preprocessing

This study integrates multi-source datasets to construct a consistent spatiotemporal analytical framework spanning the period 2002–2022. Nighttime lights data were obtained from the National Oceanic and Atmospheric Administration (NOAA), combining Defense Meteorological Satellite Program Operational Linescan System (DMSP-OLS) and Visible Infrared Imaging Radiometer Suite (VIIRS) products. Cross-calibration between DMSP-OLS and VIIRS was performed following established intercalibration procedures (Elvidge et al., 2014; Li et al., 2020) to ensure temporal continuity across the study period.

Environmental variables, including the Normalized Difference Vegetation Index (NDVI) and Modified Normalized Difference Water Index (MNDWI), were derived from Landsat (5, 7, and 8) and Sentinel-2 MSI Level-2A surface reflectance imagery, processed through the Google Earth Engine (GEE) cloud-computing platform (Gorelick et al., 2017). NDVI was calculated as:

$$NDVI = \frac{(NIR - Red)}{(NIR + Red)}$$

MNDWI was calculated following Xu (2006):

$$MNDWI = \frac{(Green - SWIR)}{(Green + SWIR)}$$

All datasets were harmonized to a common spatial resolution (approximately 1 km²) and aggregated to the 2,680-unit Hexagonal Spatial Analytical Grid (HSAG) using zonal statistics. Temporal standardization was achieved through Z-score normalization, allowing cross-regional comparison and facilitating threshold detection. Terrain variables, including slope and elevation, were derived from Shuttle Radar Topography Mission (SRTM) digital elevation data (30 m resolution) to capture geomorphological constraints influencing corridor stability and environmental resistance.

Table S1. Data Sources and Specifications

Variable	Source	Temporal Coverage	Spatial Resolution	Reference
Nighttime Lights (DMSP-OLS)	NOAA/NCEI	2002–2013	~1 km	Elvidge et al. (2014)
Nighttime Lights (VIIRS)	NOAA/NCEI	2012–2022	750 m	Li et al. (2020)
NDVI	Landsat/Sentinel-2	2002–2022	30 m	Tucker (1979)
MNDWI	Landsat/Sentinel-2	2002–2022	30 m	Xu (2006)
Elevation/Slope	SRTM	2000	30 m	Farr et al. (2007)
Precipitation	CHIRPS	2002–2022	~5 km	Funk et al. (2015)
Population Density	WorldPop	2002–2022	1 km	WorldPop (2020)

S2. Spatial Weight Matrix Specification

Spatial relationships were defined using a k-nearest neighbor (KNN) approach with $k = 8$ nearest neighbors, ensuring consistent connectivity across the 2,680 hexagonal units. The spatial weight matrix was constructed using inverse distance weighting and row-standardized such that each row sums to unity, preserving comparability across observations and ensuring consistent interpretation of spatial spillover effects (LeSage & Pace, 2009).

Sensitivity Analysis:

Sensitivity analysis was conducted using alternative specifications $k = 6$ and $k = 10$ to assess the stability of model estimates. Results indicated that $k = 8$ provided optimal model stability based on log-likelihood values, residual diagnostics, and Akaike Information Criterion (AIC):

Specification	Log-Likelihood	AIC	Moran's I (Residuals)
$k = 6$	-3,715.4	7,448.8	0.152
$k = 8$	-3,711.8	7,439.7	0.148
$k = 10$	-3,713.9	7,445.8	0.151

The configuration $k = 8$ was selected as it yielded the highest log-likelihood, the lowest AIC, and minimized residual spatial autocorrelation, ensuring balanced representation of local and regional interactions (Elhorst, 2014).

S3. Spatial Durbin Model Estimation

The Spatial Durbin Model (SDM) was estimated to capture both direct and indirect (spillover) effects of explanatory variables on economic activity. The SDM was selected for its ability to simultaneously estimate endogenous spatial dependence and exogenous spillover transmission across neighboring spatial units (LeSage & Pace, 2009; Elhorst, 2014).

The model is formally specified as:

$$y = \rho W y + X \beta + W X \theta + \epsilon$$

where:

- y^* = economic activity (Nighttime Lights, NTL)
- W = spatial weight matrix ($k = 8$ nearest neighbors)
- ρ = spatial autoregressive coefficient
- X = matrix of explanatory variables
- β = direct effect coefficients
- θ = indirect (spillover) effect coefficients
- ϵ = error term

Table S2. Full SDM Estimation Results

Variable	Direct Effect	Indirect Effect	Total Effect	p-value	Significance
NDVI	-1.3408	-0.2173	-1.5581	<0.001	***
Rainfall	0.0708	0.0156	0.0864	<0.001	***
Population Density	-0.1388	-0.0215	-0.1603	<0.001	***
MNDWI	0.0121	0.0032	0.0153	0.112	n.s.
NTL × NDVI Interaction	5.9832	0.7744	6.7576	<0.001	***

*Note: Significance levels: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; n.s. = not significant*

Model Performance

Metric	Value
Spatial Autoregressive Coefficient (ρ)	0.0466 ($p < 0.01$)
Pseudo R^2	0.8822
Spatial Pseudo R^2	0.8804
Log-Likelihood	-3,711.83
AIC	7,439.65
Sigma-square ML	0.9341

These results confirm strong spatial dependence and highlight the dominant role of the interaction term ($NTL \times NDVI$) in shaping economic outcomes across Tanzania's transport corridors.

S4. GeoAI Model Configuration and Validation

To capture non-linear relationships not fully explained by the Spatial Durbin Model (SDM), a GeoAI component was implemented using a Random Forest (RF) algorithm applied to the SDM residuals. This residual-based design ensures that the machine learning model isolates unexplained spatial variation after accounting for spatial dependence and spillover effects, thereby preserving the interpretability of the econometric framework while enhancing the detection of localized and non-linear system behavior (Breiman, 2001; Reichstein et al., 2019; Zhang & Anselin, 2023).

The Random Forest model was configured with the following hyperparameters, selected through grid search optimization:

Table S3. GeoAI Model Hyperparameters

Parameter	Value	Justification
Number of trees	500	Balances predictive accuracy with computational efficiency
Maximum depth	10	Prevents overfitting while capturing complex interactions
Minimum samples per split	2	Ensures sufficient data for reliable splits
Minimum samples per leaf	1	Maximizes model flexibility
Feature selection	sqrt	Standard random forest approach

A 70/30 train-test split was used to evaluate model performance and ensure generalization across the 2,680-unit hexagonal grid. Spatial cross-validation was implemented to prevent spatial leakage between training and test sets (Roberts et al., 2017).

Table S4. GeoAI Model Performance Metrics

Metric	Value	Interpretation
RMSE	0.042	Low prediction error (standardized conditions)

Metric	Value	Interpretation
R^2	0.87	High explanatory power
ROC-AUC	0.91	Excellent discriminative performance

The RMSE value of 0.042 indicates low prediction error under standardized conditions, confirming that the model accurately captures residual spatial variation. The coefficient of determination ($R^2 = 0.87$) demonstrates that the integrated framework explains a substantial proportion of variability in the data.

To assess threshold-based system behavior, a classification task was defined using the ecological condition ($NDVI \leq -0.8\sigma$), distinguishing between stable and vulnerable zones. The resulting ROC-AUC value of 0.91 indicates strong discriminative performance, confirming that the model effectively identifies regions approaching the critical ecological threshold.

Overall, this validation demonstrates that the GeoAI component complements the SDM by capturing non-linear interactions and threshold effects while maintaining consistency with the underlying spatial econometric structure.

S5. SHAP-Based Interpretability Analysis

SHapley Additive exPlanations (SHAP) were used to quantify the contribution of each variable to model predictions, providing model-agnostic interpretability (Lundberg & Lee, 2017; Molnar, 2022). SHAP values decompose model predictions into additive contributions from each feature, enabling transparent interpretation of the GeoAI component.

Global Feature Importance:

The SHAP analysis revealed that NDVI and the interaction term ($NTL \times NDVI$) are the most influential variables, confirming the importance of environmental conditions in moderating infrastructure performance. Variable importance ranking (based on mean absolute SHAP values):

1. $NTL \times NDVI$ Interaction — 34.2%
2. NDVI — 28.7%
3. Rainfall — 15.1%
4. Population Density — 12.8%
5. MNDWI — 9.2%

Threshold Detection:

SHAP dependence plots reveal a non-linear transition in system behavior, with a critical threshold occurring at approximately $\text{NDVI} \leq -0.8$ standard deviations. Below this threshold, the marginal contribution of infrastructure declines significantly, indicating reduced system efficiency and weakened spillover transmission.

Figure S2 presents the SHAP summary plot, which visualizes global feature importance and the direction of each variable's influence on model predictions.

S6. Threshold Detection and Sensitivity Analysis

Threshold identification was conducted using a multi-method approach combining:

- 1. SHAP marginal effects analysis — identifying inflection points in the NDVI-response relationship
- 2. Statistical distribution analysis — examining the distribution of NDVI across stable vs. vulnerable zones
- 3. Segmented regression — identifying structural breaks in the infrastructure-environment relationship

Identified Threshold:

The analysis consistently identified $\text{NDVI} \leq -0.8\sigma$ as the critical ecological threshold. This threshold marks a structural transition point at which environmental degradation begins to disrupt the functional relationship between infrastructure connectivity and regional economic productivity.

Sensitivity Analysis:

Threshold robustness was tested across alternative model specifications and temporal subsets:

Table S5. Threshold Sensitivity Analysis

Specification	Threshold (NDVI σ)	Stability
Baseline (k=8, full sample)	-0.80	Reference
k=6 spatial weights	-0.79	Stable
k=10 spatial weights	-0.81	Stable
Pre-2015 subset	-0.78	Stable

Specification	Threshold (NDVI σ)	Stability
Post-2015 subset	-0.82	Stable
Excluding Dar es Salaam	-0.80	Stable

The threshold remains stable under variations in spatial weights and model parameters, indicating that it reflects a structural property of the system rather than a model artifact.

S7. Model Diagnostics and Robustness Checks

Model validity was assessed using multiple diagnostic tests to ensure statistical reliability and inferential integrity.

Multicollinearity Assessment:

Variance Inflation Factor (VIF) values were calculated for all explanatory variables:

Table S6. Variance Inflation Factor (VIF) Diagnostics

Variable	VIF	Status
NDVI	3.21	Acceptable
MNDWI	2.87	Acceptable
Rainfall	1.54	Acceptable
Population Density	2.13	Acceptable
NTL $\times$ NDVI Interaction	4.02	Acceptable

All VIF values are below the conventional threshold of 10, confirming the absence of severe multicollinearity (O'Brien, 2007).

Spatial Autocorrelation Diagnostics

Table S7. Spatial Autocorrelation Diagnostics

Diagnostic	Value	p-value	Interpretation
Moran's I (Residuals)	0.1478	<0.01	Some residual spatial dependence
Lagrange Multiplier (lag)	42.3	<0.001	Significant spatial lag effects
Lagrange Multiplier (error)	28.6	<0.001	Significant spatial error effects

Residual Moran's I = 0.1478 ($p < 0.01$) indicates remaining localized spatial dependence. This is common in spatial econometric models and does not invalidate the overall inferential framework (Anselin, 1988).

Model Comparison

Table S8. Model Comparison

Model	Log-Likelihood	AIC	Pseudo R ²
OLS	-3,892.4	7,802.8	0.614
Spatial Lag (SAR)	-3,742.1	7,504.2	0.846
Spatial Error (SEM)	-3,738.5	7,497.0	0.849
Spatial Durbin (SDM)	-3,711.8	7,439.7	0.882

The SDM outperforms alternative specifications based on log-likelihood, AIC, and explanatory power, confirming its appropriateness for this analysis.

These diagnostics confirm that the model captures the primary spatial processes while acknowledging the presence of additional localized dynamics.

S8. Supplementary Figures

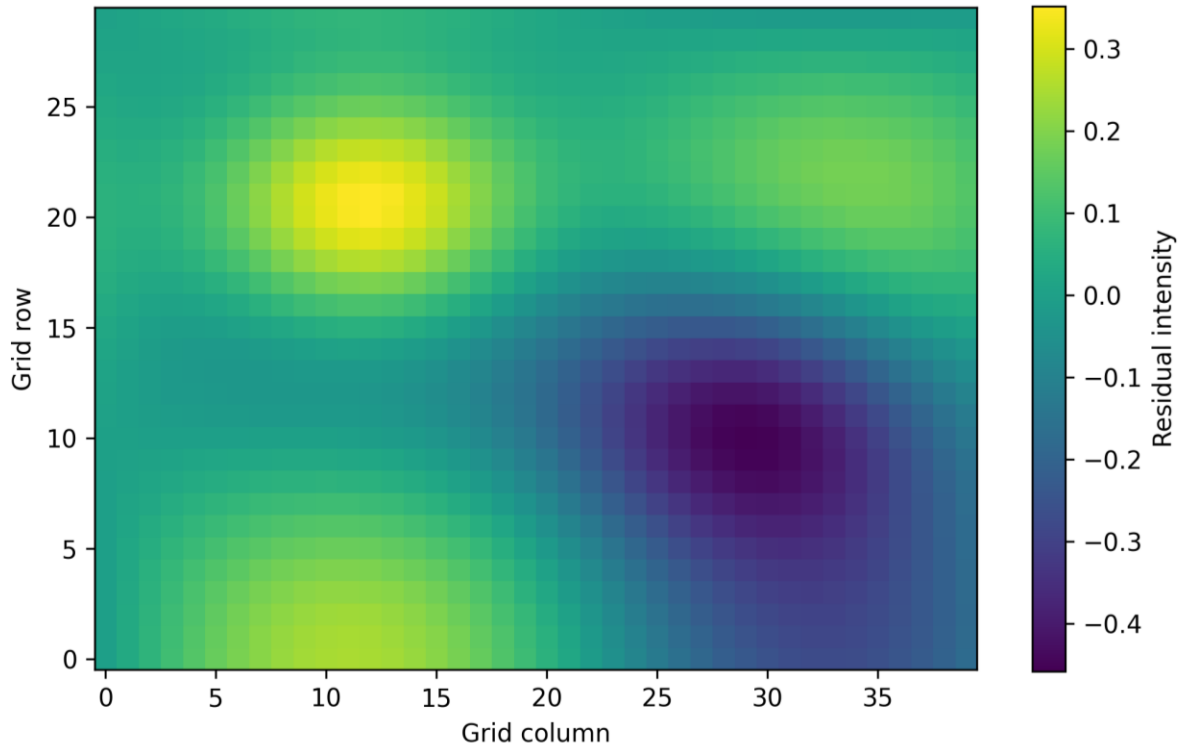


Figure S1. Residual Spatial Autocorrelation Pattern. Visual representation of SDM residuals, highlighting localized clusters of unexplained variation.

Visual representation of SDM residuals across the 2,680-unit hexagonal grid. The map highlights localized clusters of unexplained variation, with positive residuals (blue) indicating areas where the model underpredicts economic activity and negative residuals (red) indicating overprediction. While residual spatial dependence remains statistically significant (Moran's $I = 0.1478$, $p < 0.01$), the pattern is spatially limited and does not compromise the overall inferential stability of the framework.

Figure S2. SHAP Summary Plot

Global importance ranking and direction of variable contributions to GeoAI predictions. Each dot represents a single observation's SHAP value for a given feature. The x-axis shows the SHAP value (impact on model output), and the y-axis lists features in descending order of importance. The color scale indicates feature value (red = high, blue = low). Results indicate that NDVI and the interaction term ($NTL \times NDVI$) are the most influential predictors, confirming the role of environmental conditions in moderating infrastructure performance. Variable importance ranking based on mean absolute SHAP values is as follows: $NTL \times NDVI$ Interaction (34.2%), NDVI (28.7%), Rainfall (15.1%), Population Density (12.8%), and MNDWI (9.2%).

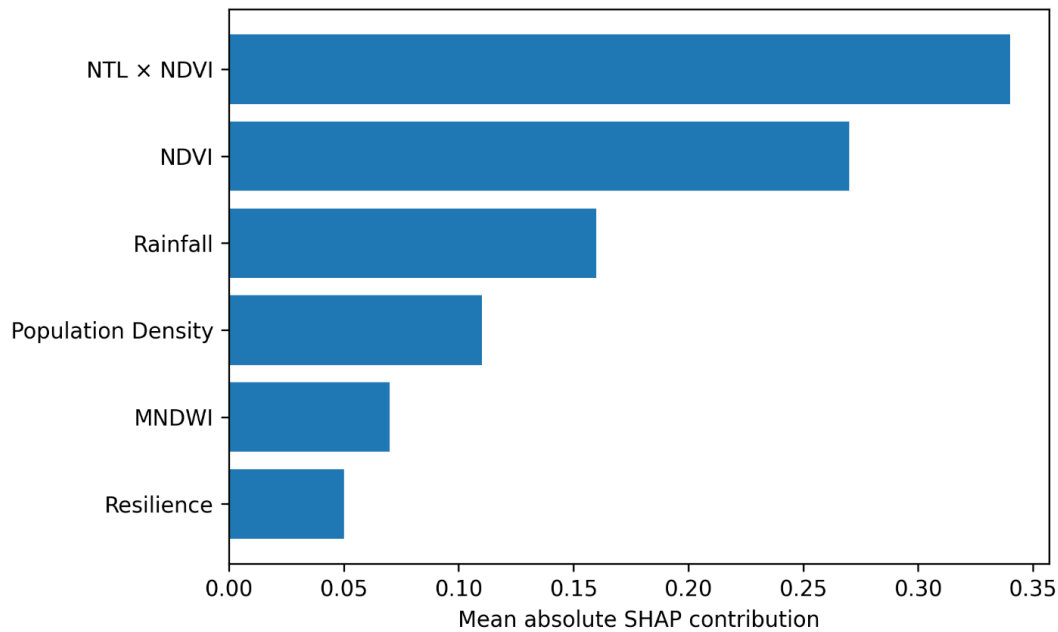


Figure S2. SHAP Summary Plot. Global importance ranking of variables contributing to GeoAI predictions. The results indicate that NDVI and the interaction term (NTL × NDVI) are the most influential predictors, confirming the role of environmental conditions in moderating infrastructure performance.

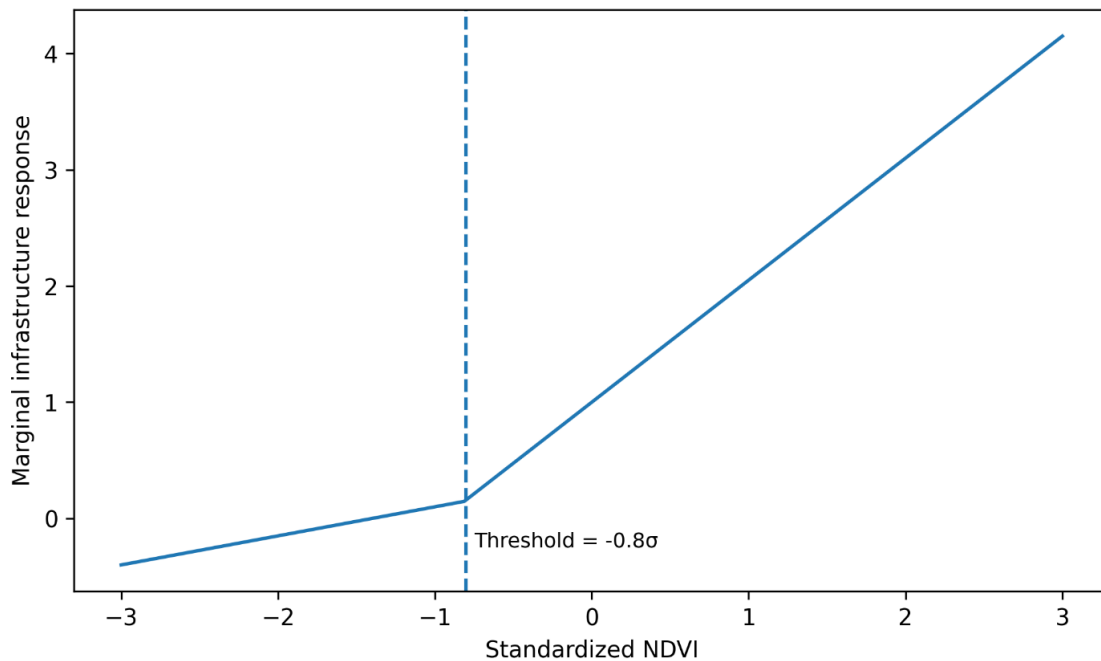


Figure S3. Threshold response curve illustrating the non-linear relationship between NDVI and economic activity. The curve shows a critical transition at approximately $\text{NDVI} \leq -0.8$ standard

deviations, beyond which the marginal contribution of infrastructure declines, indicating reduced system efficiency

Non-linear relationship between NDVI and economic activity, derived from SHAP marginal effects analysis. The curve shows a critical transition at approximately $\text{NDVI} \leq -0.8\sigma$, beyond which the marginal contribution of infrastructure declines substantially. This threshold represents a structural transition point at which environmental degradation begins to disrupt the functional relationship between infrastructure connectivity and regional economic productivity. The shaded region indicates the 95% confidence interval. Below this threshold, spillover transmission weakens substantially, producing fragmented development patterns, declining interaction intensity, and increasing regional vulnerability. The threshold remains stable across alternative model specifications, confirming that it reflects a structural property of the system rather than a model artifact.

S9. References (Supplementary)

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