Assessment of economic well-being in South Africa based on remote sensing transfer learning

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Abstract

Persistent socio-economic and environmental inequalities pose major challenges to sustainable development in the global South. However, comprehensive and spatially clear data on environmental conditions and socio-economic well-being remain scarce, preventing a thorough analysis of intersecting inequalities. This study assesses economic well-being and its relationship to environmental factors in South Africa by proposing a method for analysing environmental and socio-economic inequalities using remote sensing data and transfer learning, using publicly available satellite imagery and statistics. We take the established correlation between nighttime light intensity and economic activity and propose a framework to analyze it in parallel with environmental indicators derived from daytime satellite imagery. Our approach centers on training convolutional neural network (CNN) models to extract economic and environmental features from high-resolution daytime satellite data. CNNS are trained to predict nighttime light intensity, act as proxies for economic activity, while learning to recognize environmental features. Patterns indicating economic activity and environmental conditions can be identified from daytime images alone. By linking the extracted features to known socio-economic indicators obtained from census data and surveys, a spatially clear map of South Africa's economic well-being and environmental quality was created.

1. Introduction

Inequality is a persistent social problem around the world. High inequality can have serious negative effects on economic productivity, environmental burden distribution, etc(Boyce, 1994; Jensen, 1975; Pandey et al., 2022). To address inequality effectively, it is essential to develop comprehensive economic policies and accurately assess their effectiveness.

In recent years, countries have gradually shifted from a single focus on economic levels to the pursuit of broader and more sustainable well-being in the development process, and have actively sought more appropriate evaluation indicators to measure social progress. Stiglitz et al. (2009), for example, advocates for a multidimensional approach to measuring economic progress, encompassing not only GDP but also household disposable income, income distribution, environmental quality, health, and education. This reflects an evolving understanding of development, one that prioritizes holistic human development and improved well-being alongside economic growth.

Economic well-being, as one of the core indicators to measure the economy, reflects the level of economic development in various places. Accurate assessment of economic well-being is therefore key to developing effective economic policies, timely monitoring of economic inequality, and achieving sustainable development. The traditional methods of economic well-being evaluation mainly rely on social survey and statistical data, and comprehensively evaluate economic well-being by constructing index system. However, when it comes to large-scale economic well-being assessments, the traditional survey data presents problems such as limited data, time lag(Tiago et al., 2017), and insufficient spatial coverage to support large-scale assessments, which hinder thorough analysis of these intertwined inequalities. The satellite remote sensing technology can obtain the surface information through the sensor mounted on the satellite, and convert it into images or data for analyzing and studying various phenomena of the earth. It has the characteristics of large observation area, strong timeliness and strong periodicity. In the assessment of economic well-being, satellite remote sensing data can provide spatial information at local, regional and global scales to support relevant decision-making.

Transfer learning is a machine learning technique that uses a model trained on one task to improve the performance of another related task, thereby reducing the amount of training data required for the target task and improving the model's generalization ability. In economic well-being assessment, transfer learning methods can apply existing economic well-being assessment models to new regions or new data sources, for example, applying models trained in developed countries to developing countries, thereby overcoming the problem of data scarcity, and improving the applicability and prediction accuracy of models.

Because of the strong correlation between night light data and economic activity, some studies have used night light data as a proxy indicator of economic development, training deep learning models on daytime images to predict the level of night light intensity and thus indirectly predict economic well-being.
Xie et al. (2016) proposed a transfer learning approach that uses nighttime light intensity as a proxy for economic activity and trains a fully convolutional CNN model to predict nighttime light from daytime images while learning features useful for poverty prediction. The model simultaneously predicts nighttime light levels and extracts spatially explicit features relevant to poverty mapping, and achieves 71.58% validation accuracy within 223,500 iterations, demonstrating efficient convergence without spatial cropping. Based on this, Ni et al. (2021) conducted experiments using four different deep learning models to verify the feasibility and effectiveness of the method of predicting poverty through deep learning using night data as a proxy. Liu et al. (2021) used nighttime light remote sensing data as a proxy for socio-economic indicators, constructed a label for night light intensity levels in daytime satellite images, and trained the attention-enhanced VGG-16 network as a feature extractor to estimate county-level GDP in China using both day and night remote sensing data. NTL labels focus on effective regions through transfer learning constraints

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and reduce overfitting of irrelevant ground objects (such as farmland textures), which improves model generalization ability. This method achieved an R^2 of 0.71 for county-level GDP estimation, a 0.04 improvement in R^2 compared to the model without NTL guidance, without significantly increasing model complexity.

Here, we use a method to analyze environmental and socio-economic inequalities in South Africa using remote sensing data and transfer learning to extract socio-economic data from daytime satellite imagery. This approach allows us to take advantage of the wealth information contained in remote sensing data, even in areas where labeled data is limited. We use a multi-step transfer learning strategy to improve the efficiency and accuracy of the model. Pre-trained CNNs have become proficient at identifying general image features and fine-tuning the specific context of South Africa in conjunction with publicly available socioeconomic statistics and satellite imagery. The model effectively acts as a powerful feature extractor, identifying patterns that indicate economic activity and environmental conditions from daytime images alone. This reduces the reliance on costly and space-limited ground surveys. By linking extracted characteristics to known socioeconomic indicators (such as access to services) derived from census data and surveys, we can create spatially clear maps of economic well-being and environmental quality. Remote sensing data combined with socio-economic statistics can provide a fuller and more nuanced picture of these inequalities than traditional methods alone.

2. Research Data

2.1 Remote sensing data

The remote sensing data (Figure 1) used in this study came from the remote sensing images obtained by Landsat 8 satellite. Landsat 8 is equipped with Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS) sensors, capable of providing multispectral data across 11 spectral bands with a spatial resolution of 30 meters. The images cover the South African region, and the data span from January 2024 to March 2025, and all images are obtained through the Google Earth Engine (GEE) platform.

In order to ensure the reliability of the research results, the image with less than 10% cloud cover is preferentially selected to reduce atmospheric interference, and the required six bands are extracted, covering the range of visible light to short-wave infrared spectrum, and the target region of South Africa is extracted through Mosaic and cropping. Landsat 8 data, due to its long-term continuity, open access policy and medium-high spatial resolution, provided reliable data support for this study's analysis of regional economic well-being assessment in South Africa.

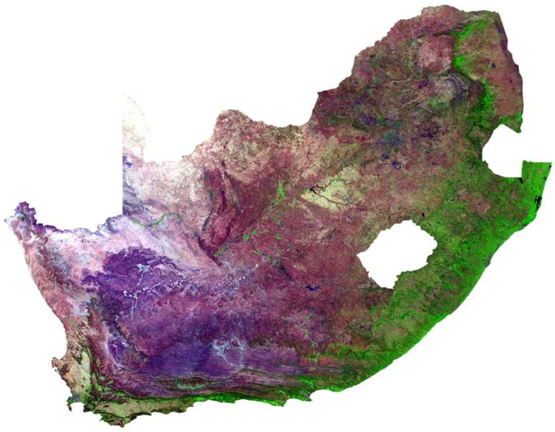


Figure 1. Remote sensing image of South Africa from Landsat 8 satellite, False Color Composite (Bands 6-5-4) displayed in SWIR-1, NIR, Red combination (R-G-B channels).

2.2 Statistical data

This study used statistics from The National Treasury, including monitoring and reporting of local government finances from July to December 2024. We took five indicators from the report as a proxy for local economic well-being, as shown in Table 1. The five indicators are Property rates, Service charges - Electricity, Service charges - Water, Community and Public Safety (including Community and Social Services, Sport and Recreation, Public Safety, Housing and Health) and Economic and Environmental Services (including Planning and Development, Road Transport and Environmental Protection). Using Metropolitan and Local municipalities as the data collection scale, a total of 199 regions had specific and complete data.

Statistical data	**Property rates**	
	Service charges - Electricity	
	Service charges - Water	
	Community and Public Safety	Community and Social Services
		Sport And Recreation
		Public Safety
		Housing
		Health
	Economic and Environmental Services	Planning and Development
		Road Transport
		Environmental Protection

Table 1. Statistical data

3. Research methods and processes

Research method and process: The research method mainly includes three core contents, which are the economic feature extraction model of remote sensing image based on transfer learning, the construction of economic well-being parameters and regression analysis.

3.1 Economic feature extraction model of remote sensing image based on transfer learning

In this study, a deep learning framework combining transfer learning and Low-Rank Adaptation (LoRA) is constructed to extract implied economic features from daytime multispectral remote sensing images. As shown in Figure 2, the model training process includes three core modules: data preprocessing, feature encoder construction, and lightweight fine-tuning.

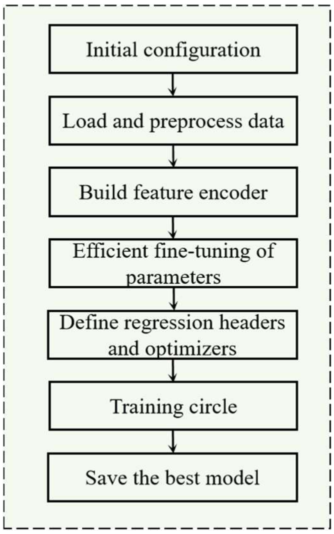


Figure 2. the model training process

3.1.1 Data preprocessing and enhancement: The experimental data were obtained from the Landsat 8 multispectral imaging chip in South Africa, covering the range of visible light to short-wave infrared spectrum. The radiation value is standardized. In order to improve the robustness of the model to light conditions and seasonal changes, random geometric transformation (horizontal/vertical flip, probability p=0.2) and radiation perturbation (brightness Δ±10%, contrast Δ±10%) were introduced to construct a dynamic data enhancement strategy.

3.1.2 Model architecture and transfer learning: The backbone network uses ResNet50 pre-trained by ImageNet to output high-dimensional semantic features through feature pyramid. To solve the channel mismatch problem between multi-spectral data and RGB model pre-trained by ImageNet, a learnable 1×1 convolutional adaptation layer is designed to project the 6-channel input into 3-dimensional space. Based on LoRA technology, 95% of the original parameters are frozen, and only low-rank matrix (rank r=8, scaling factor α=32) is injected into the ResNet residual block, reducing the number of trainable parameters to less than 0.5% of the original model.

After the training is completed, the regression head is removed and the high-dimensional feature vector of the backbone network output is extracted to represent the hidden economic features in the image. The model architecture diagram is shown in Figure 3.

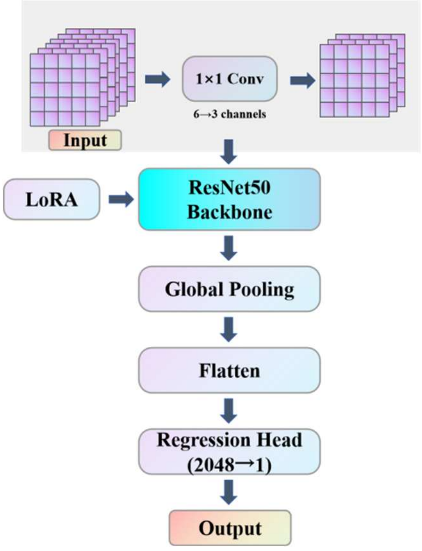


Figure 3. model architecture diagram

3.2 Construction of economic well-being parameters

By linking the extracted features to known socio-economic indicators (e.g., income, education, access to services) obtained from census data and surveys, we can create spatially explicit maps of economic well-being and environmental quality. Given the scarcity of national statistics and indicators, we extracted valid data from local government finances, which are monitored and reported on a quarterly basis by the South African National Treasury, and synthesized economic well-being parameters.

3.2.1 Data selection: In order to construct comprehensive economic indicators associated with remote sensing features, this study used Principal Component Analysis (PCA) to generate comprehensive economic well-being parameters based on five local government fiscal revenue and expenditure data released by the South African National Department of Finance (Table 1). This parameter will be used as the core target variable for subsequent regression analysis. The five selected indicators cover the multi-dimensional characteristics of local economic development:

Property rates: reflect the level of regional asset values;
Service charges - Electricity: represents the intensity of infrastructure supply and the energy demand of economic activities;
Service charges - Water : reflects water resources management and public service expenditure;
Community and Public Safety : covers social welfare, housing security and policing expenditures, and measures the capacity of government public services and local living conditions;
Economic and Environmental Services: includes investment in planning and development, transportation construction and environmental protection, reflecting the sustainable development potential of the region.

These five types of indicators comprehensively reflect the regional economic scale, resource allocation efficiency and public service level through the structure of fiscal expenditure, and reflect the local economic situation from multiple dimensions.

3.2.2 Principal component analysis and parameter generation: The cumulative variance contribution threshold method was used to determine the number of principal components, calculate the eigenvalues and contribution rates of the correlation coefficient matrix, and retain the principal components with cumulative contribution rates ≥95%. Based on the results of principal component analysis, the first three principal components cumulatively explain 99.4% of the variance of the original data, indicating that they can effectively characterize the multidimensional characteristics of the local economy in South Africa.

Among them, the first principal component (PC1) explains 83.65% of the variance and its load matrix shows a positive correlation (Table 1). Property rates (PropRate: 0.990) load is near saturation, reflecting the core revenue source of local finances, water (SvcWtr: 0.974) is highly correlated with electricity service charges (SvcElec: 0.955), indicating the scale of infrastructure services, and community safety (ComSafe: 0.955). 0.898) in tandem with economic environment Services (EcoEnv: 0.746). PC1 can be interpreted as the "basic economic scale index", which comprehensively quantifies regional fiscal capacity, public service supply level and infrastructure investment.

Principal component	PC1	PC2	PC3
Explanatory variance ratio	83.65%	10.58%	5.12%
SvcWtr	0.974	-0.176	0.099
SvcElec	0.955	-0.227	0.192
PropRate	0.99	-0.103	0.048
ComSafe	0.898	-0.004	-0.446
EcoEnv	0.746	0.662	0.097

Table 2. Explanatory variance ratio and full load for the first three principal components

Property rates have the highest load in PC1 (0.99) and are the core proxy variable for regional economic levels; Economic and environmental services are gaining prominence in PC2 (0.66), reflecting local differences in sustainable development policies; Community and Public Safety is negatively dominant (-0.45) in PC3, suggesting a regional imbalance in the structure of public spending.

Using Min-Max standardization, the PC1 score is linearly mapped to the interval [0,1] to generate comparable economic parameters:

$$\mathrm{EconParam_i} = \frac{\mathrm{PC1_i} - \min(\mathrm{PC1})}{\max(\mathrm{PC1}) - \min(\mathrm{PC1})} \tag{1}$$

The economic parameters generated by this method have both statistical significance and economic explanatory power, and the larger the value of the parameter, the stronger the regional basic economic scale, which provides a robust reference variable for the subsequent remote sensing feature regression.

3.3 Regression

3.3.1 Scale unification of multi-source data: We use spatial aggregation technology to realize the scale unification of multi-source data. Aiming at the integration of economic statistical data (administrative division scale) and remote sensing features (grid scale), the geographical weighted statistical method is used to carry out data coupling: Firstly, based on the vector boundary of administrative divisions, the raster feature statistics (mean value, standard deviation, 25% and 75% quantile) in each administrative unit are calculated using zonal statistics algorithm, and the feature data set matching with administrative divisions is generated.

3.3.2 Regression analysis model: A quantitative relationship model between remote sensing economic characteristics and integrated economic parameters (EconParam) is established by using random forest regression model. Based on the actual data verification, the model shows remarkable ability to predict economic parameters.

Based on 199 cities with existing data, the optimal combination of hyperparameters is determined through grid search: number of decision trees, maximum depth, and minimum number of split samples. Excellent performance was obtained on 159 training samples and 40 test samples. In the test set, R^2=0.793, RMSE=0.066, indicating that the model could explain 79.3% of the economic parameter variation.

3.3.3 Feature importance analysis: The feature importance analysis based on Gini impurity reduction method reveals (Figure 4):

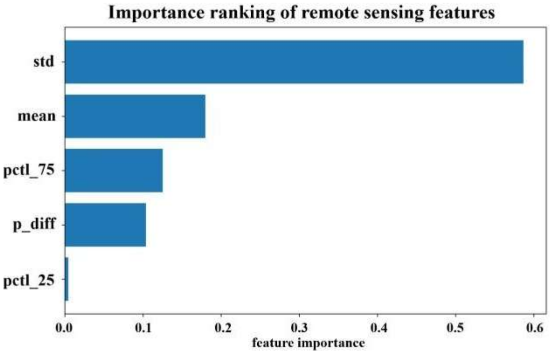


Figure 4. Importance ranking of features

Spatial heterogeneity (std): The contribution degree is 58.7%, indicating that land cover complexity is the core index of economic parameter prediction.

Mean spectral intensity (mean): 18.0% contribution, reflecting the positive correlation between economic activity intensity and spectral reflectance.

High-digit difference: the joint contribution was 22.9% (pctl_75=12.5% + p_diff=10.4%), reflecting the predictive value of the regional distribution of hyperspectral values.

Low quantile (pctl_25): the contribution is only 0.4%, indicating that the lower limit of the spectrum is less sensitive to economic parameters.

4. Results

4.1 Nighttime light intensity extraction of remote sensing image

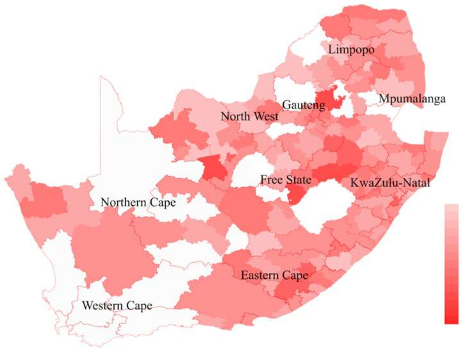
The trained model was applied to the whole country of South Africa to predict the nighttime light intensity of South Africa, as shown in Figure 5:

Figure 5. Nighttime light of South Africa extracted from daytime remote sensing images

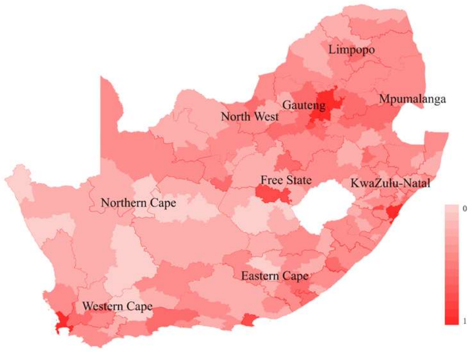
4.2 Economic parameter forecasting

4.2.1 Model prediction effect: Among the 40 test samples, the prediction results of the model are highly consistent with the real values, and the accuracy parameters are: R^2 =0.793, RMSE=0.066 (standardized parameter range $[0,1]$), showing strong prediction ability.

4.2.2 The final forecast results: In Figure 6 (a) is the original statistical data distribution map, where the uncolored parts are the cities where the statistics are missing. In Figure 6 (b) is the final forecast result. The two figures show that the method can better predict economic parameters and make up for the lack of statistical data.



(a)



(b)

Figure 6. (a)the original statistical data distribution map

(b) Economic parameter forecast distribution map

On the whole, Gauteng Province, KwaZulu-Natal Province and Western Cape Province show a high economic level, while the Northern Cape province has a relatively low economic level.

4.2.3 Typical regional analysis: As the economic center of South Africa, Gauteng province is the largest contributor to the economic output of South Africa. In the economic parameter prediction, the Gauteng city cluster with Johannesburg - Pretoria as the core forms a continuous high-value area.

Cape Town's economic parameters are also predicted to be higher, as South Africa's second largest city. Cape Town is the economic center of the Western Cape Province, and the second largest economic center in South Africa after Johannesburg. Cape Town is located at the intersection of important international waterways, with excellent ports and the largest dry dock in the Southern Hemisphere.

The Northern Cape's economy has long been dominated by agriculture, mining, and the small processing industries associated with them. Due to its remote location, lack of water resources and low level of education of the working population, there is little foreign investment and economic development is slow and below the national average. The forecast of its economic parameters also shows a low level.

5. Discussion

Economic well-being assessments are essential to address the socio-economic and environmental inequalities that exist. By providing large-scale, frequent, and spatially detailed data, remote sensing overcomes traditional limitations and reveals new perspectives on well-being that were previously unobservable. Beyond simply quantifying economic activity, remote sensing data contributes to a deeper understanding of the intricate interrelationships between environmental conditions, infrastructure development and human well-being. Machine learning and deep learning techniques further amplify these capabilities. Together, these technologies improve forecast accuracy while enhancing scalability, enabling decision-makers to efficiently access practical solutions across a wide geographic area. By simplifying the analysis process, these tools enable decision makers to turn complex data into timely, large-scale interventions.

Using publicly available satellite images and statistics, we use established correlations between nighttime light intensity and economic activity to identify patterns indicative of economic activity and environmental conditions from daytime images alone. This reduces the reliance on costly and space-limited ground surveys. By linking extracted features and readily available socioeconomic indicators, we can create spatial maps of economic well-being and environmental quality, identifying areas of inequality where socioeconomic disparities and environmental vulnerability are heightened through analysis of spatial distributions. Our analysis aims to shed light on the complex interplay between socio-economic status and environmental conditions, providing insight into the drivers of inequality in South Africa. Remote sensing data combined with socio-economic statistics can provide a fuller and more nuanced picture of these inequalities than traditional methods alone.

Deep learning methodologies offer significant promise for extracting complex patterns and making accurate predictions from remote sensing data. Looking ahead, several challenges need to be addressed to fully realize their potential. The issue of data scarcity and potential unreliability of ground truth data remains a significant bottleneck for training robust and generalizable deep learning models (Burke et al., 2021). Another important direction is to improve remote sensing indicators to reflect the multifaceted nature of economic inequality. The strategic integration of these metrics with traditional socioeconomic data, coupled with continued advances in machine learning and artificial intelligence, promises to unlock more refined and dynamic assessments.

Future work should be further carried out to: 1) Improve remote sensing indicators to capture various aspects of economic well-being. 2) Improve the scale of economic well-being assessments to enable more refined analysis to support detailed policy formulation. 3) Improve the transferability of deep learning models, especially their interpretability (Roscher et al., 2020), to enhance credibility and promote policy adoption.

Overall, the study shows the potential of remote sensing and transfer learning as powerful tools for analyzing environmental and socioeconomic inequalities in the Southern Hemisphere. The findings provide valuable information to policymakers and development practitioners in South Africa, enabling them to target interventions in vulnerable areas to promote sustainable development and reduce inequalities. The scalability and cost-effectiveness of this approach makes it easily transferable to other regions facing similar challenges, contributing to a broader understanding of the complex relationship between environment and society in pursuit of a more equitable and sustainable future for the global South.

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