

1. Introduction

- Poverty is a complex phenomenon that requires extensive research to comprehend the severity and impact it has in a community. This research will demonstrate how deep learning coupled with statistical regression modelling can be used to estimate poverty on aerial images supplemented with national household survey data.
- Data collected in KwaZulu-Natal (KZN), South Africa was used because of the heterogeneous nature of the data.

2. Objectives

- Train a deep learning convolutional neural network (CNN) model to detect dwelling types (brick house, traditional house, and informal house) and geo-types (urban, rural, and farm) from aerial images.
- Train a statistical regression model that estimates the poverty index, Sen-Shorrocks-Thon index (SST), from the detected dwelling types and geo-types in the aerial images.

3. Methodology

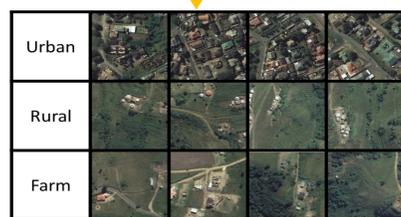
Phase 1: Aerial Classification and Detection

Step 1: Manual label dwelling types and geo-types from 300x300 images using labelme.py.

Step 2.1: Dwelling type detection: Train a Mask R-CNN model [1].



Step 2.2: Geo-type classification: Train InceptionV4 [2].



Step 3: Aggregate Results: Create a cross-tab of the detected dwelling types found within each geo-type.

Dwelling Type	Geo-Type			
	Urban	Rural	Farm	
Brick House	89	50	64	
Traditional House	13	91	20	
Informal Settlement	90	82	45	

Proportionate & vectorise

Brick House Urban	Brick House Rural	...	Informal Settlement Rural	Informal Settlement Farm
0.44	0.25	...	0.38	0.21

Phase 2: Poverty Modelling

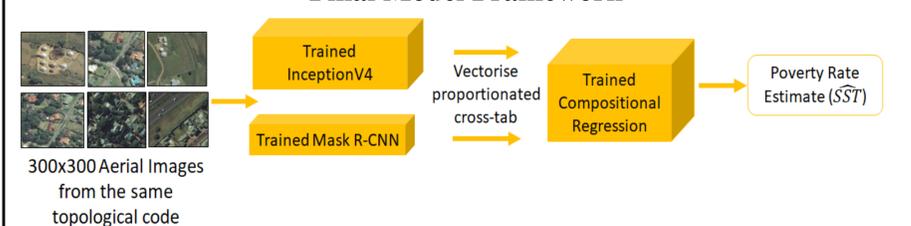
Step 4: Prepare Survey Data – NIDS Survey Data Wave 3 (2012):

- Group households by topological codes.
- Calculate the poverty rate, SST, for each topological code.
- Vectorise a cross-tab of the dwelling type within each geo-type from the survey data.

Step 5: Model the poverty rate, SST, on the proportion of dwelling types found within each geo-type by training compositional regression model [3].

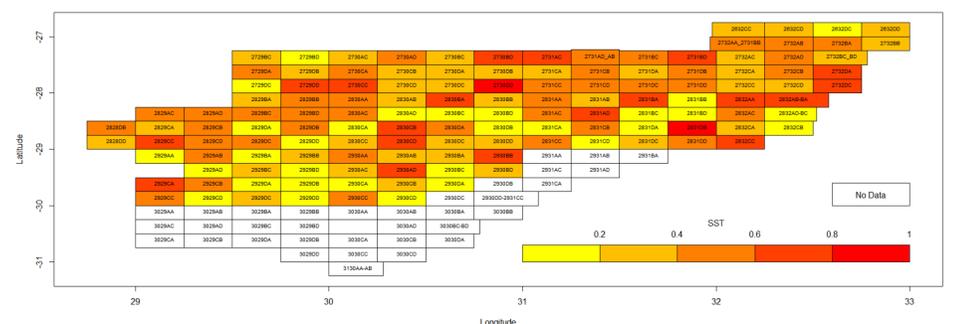
Step 6: Create a final model framework for estimating poverty using aerial images.

Final Model Framework

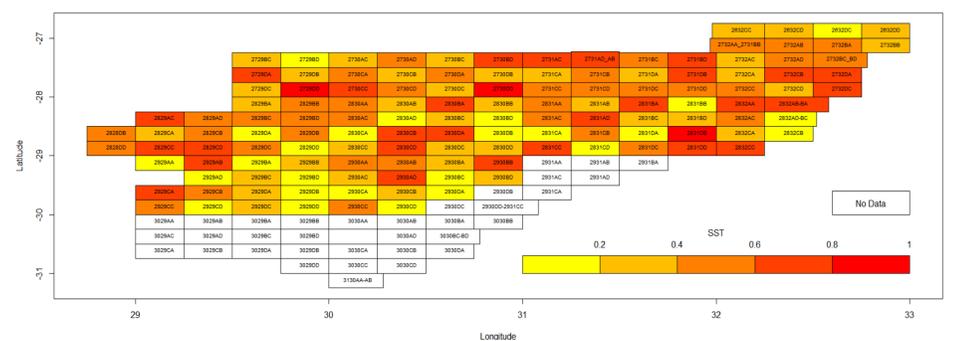


4. Results

- Phase 1: The dwelling type detection model obtained a mean Average Precision (mAP) of 0.665, while the geo-type classification model obtained a loss of 0.2970.
- Phase 2: The poverty modelling model obtained an R-squared of 0.6307.
- The final model was able to estimate the SST distribution of KZN, as shown in Figure 2.
- The performance of the final model suggests that poverty levels can be inferred from aerial images.



(a) Estimated SST distribution



(b) Actual SST distribution

Figure 2: Sen-Shorrocks-Thon (SST) index distribution map in KwaZulu-Natal, where (a) is the estimated distribution and (b) is the actual distribution obtained from National Income Dynamic Study (NIDS) Wave 3 (2012) survey data.

5. Conclusion

- This approach displays great potential in becoming a supplementary tool that the government can use to efficiently measure, monitor and analyse the poverty rate as they implement policies targeted to alleviate poverty.

Figure 1: Method design for poverty estimation from aerial images.

References:

[1] He, K., Gkioxari, G., Dollar, P., and Girshick, R. B., (2017). Mask R-CNN. *CoRR abs/1703.06870*

[2] Szegedy, C., Ioffe, S., Vanhoucke, V., Alemi, A. A., Inception-v4, inception-resnet and the impact of residual connections on learning. *CoRR, abs/1602.07261*.

[3] Alenzi, A., (2019). Regression for Compositional Data with Compositional Data as Predictor Variables With or Without Zero Values. *Journal of Data Science, 17(1). P.219-238*