VALUE OF INFORMATION AND TRADE-OFF ANALYSIS FOR RURAL ROAD INVESTMENT FRAMEWORKS: NEW INSIGHTS FROM MCA SENSITIVITY, WASTE PER ROAD, AND CLUSTER STABILITY

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ABSTRACT

Governments in low-income countries often spend millions upgrading rural roads that yield negative economic returns, yet simpler decision tools risk leaving isolated communities without access. This paper extends our previous comparison of four decision methods for 166 rural roads in Sri Lanka with five new analyses. Value of Information (VoI) measures the extra economic benefit of using full integer linear programming (ILP) instead of PCA-clustering. The gain is largest at high budgets (Rs.400M at 100%) but only exceeds a hypothetical full evaluation cost (Rs.332M) at the 100% budget. Multi-criteria analysis (MCA) weight sensitivity shows that giving 50% weight to the benefit-cost ratio achieves the highest accuracy (92.8% at 25% budget), while condition-heavy weighting (IRI = 50%) performs poorly (38.3%). Waste per negative-NPV road is zero for PCA-clustering until the 55% budget, then rises to Rs.5.9–9.2M, whereas IRI ranking wastes Rs.19–69M per bad road. Cluster stability reveals a clear split: roads are funded either at 40% or only at 70% budget, confirming that PCA-clustering separates investable from non-investable roads. The results support a pragmatic rule: for budgets up to 40%, PCA-clustering or economic-heavy MCA deliver near-optimal efficiency and higher population reach; full ILP is justified only when economic data are already available, or the budget is very high (85%).

Keywords: rural road investment, PCA clustering, multi-criteria analysis, value of information, cluster stability

1. INTRODUCTION

Rural roads connect villages to schools, hospitals, and markets. Yet across low-income countries, road upgrading decisions are often made using rough rules of thumb-such as fixing the worst roads first-which frequently fund projects that destroy value. In a dataset of 166 Sri Lankan rural roads, 58.4% have negative net present value (NPV); an unconstrained strategy would waste Rs.9,689million. Agencies thus face a dual challenge: avoiding wasteful over-investment while serving dispersed populations.

In our earlier work, we compared four frameworks-condition-based ranking by road roughness (IRI, F1), multi-criteria analysis (F2), PCA-clustering (F3), and integer linear programming optimization (F4)-across six budget levels. This extended abstract adds five new analyses: Value of Information (VoI), detailed sensitivity testing of MCA weights, waste per bad road, cluster stability, and a multi-dimensional trade-off assessment. These provide practical guidance for agencies with limited data and resources.

2. LITERATURE REVIEW

Condition-based heuristics dominate rural road management but fail to capture economic returns (Harvey, 2024). Multi-criteria analysis incorporates multiple indicators, but weight selection remains subjective (Ramachandran et al., 2019). Data-driven methods, particularly PCA with

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k-means clustering, have been used for pavement condition prediction (Liu et al., 2022). ILP optimization offers theoretical optimality but demands high-resolution data (Liu et al., 2022).

Existing comparative studies focus on technical performance in isolation, not on accuracy per resource cost or population reach. This study fills that gap with five new quantitative insights.

3. METHOD

The dataset (166 rural roads) is described in Pasindu (2025). Frameworks: F1 ranks by IRI; F2 uses a weighted composite score (IRI 30%, ADT 20%, Pop_per_inv 25%, BC ratio 15%, maintenance net benefit 10%); F3 applies PCA (four components, 87.1% variance) and k-means (k=4), then funds clusters by mean NPV; F4 solves a binary knapsack maximizing NPV.
For each budget level (25–100% of positive-NPV total), we computed: VoI = NPV(F4) NPV(F3); extended MCA sensitivity (four weight schemes); waste per road = total waste (Rs. spent on negative-NPV roads) divided by number of such roads funded; first funding budget for F3; and accuracy, population coverage, and positive road percentage for all frameworks. Calculations used Python (pandas, scikit-learn, PuLP, matplotlib).

4. RESULTS AND DISCUSSION

4.1. Value of Information (VoI)

Figure1 plots the NPV gain from upgrading F3→F4. Gains are: Rs.332M (25%), Rs.46M (40%), Rs.290M (55%), Rs.258M (70%), Rs.316M (85%), Rs.400M (100%). A hypothetical full evaluation cost (Rs.2M per road × 166 = Rs.332M) is shown as a dashed line. This Rs.2M per road is an illustrative figure based on typical engineering survey, traffic counting, and economic analysis costs in Sri Lanka (readers should adjust using local rates). Only at the 100% budget does the VoI clearly exceed this cost. Upgrading is most justified at high budgets; at lower budgets the gain is comparable or lower, making the decision context dependent.

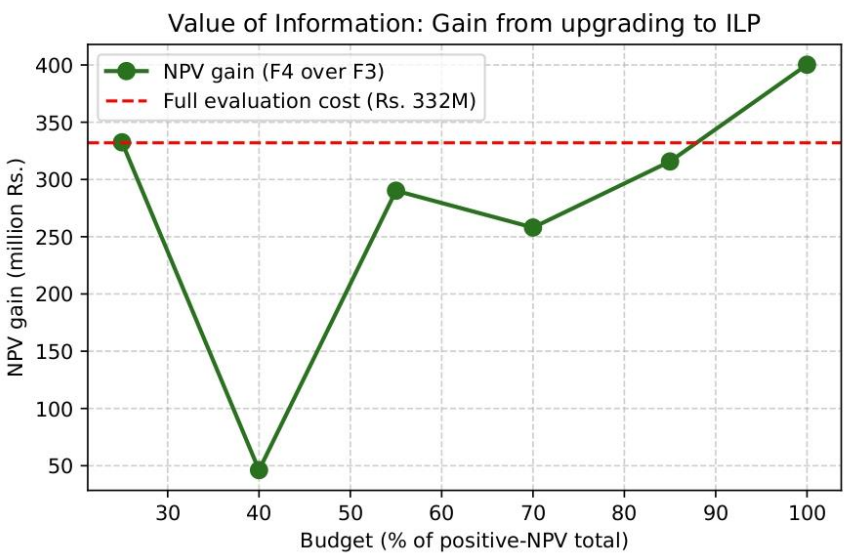

Figure 1. Value of Information: NPV gain from upgrading F3→F4. Dashed line: illustrative evaluation cost Rs.332M

4.2. Extended MCA Weight Sensitivity

Figure 2 shows F2 accuracy under four weight schemes across six budgets. Economic-heavy weighting (BC ratio = 50%) achieves the highest accuracy at every budget (92.8% at 25%, 87.4% at 40%, etc.). Condition-heavy weighting (IRI = 50%) never exceeds 70%. Baseline and equal weights are intermediate. Weight selection dramatically affects outcomes; giving high weight to the benefit-cost ratio is strongly beneficial at all budget levels.

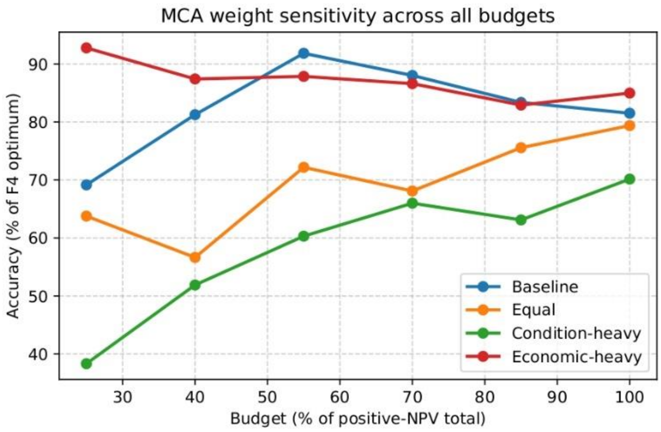

Figure 2. MCA weight sensitivity across all budgets. Economic-heavy weighting (BC ratio = 50%) consistently outperforms others. (Ramachandran et al., 2019)

4.3. Waste per Negative-NPV Road and Cluster Stability

Figure3 shows average waste per negative-NPV road. F1 wastes Rs.19–69M per bad road (highest at 25% budget). F2 keeps waste very low (Rs.2M at 25%, rising to Rs.28M at 100%). F3 has zero waste until the 55% budget, then waste appears (Rs.5.9–9.2M)—by design, because it funds only the high-return cluster first. F4 has zero waste at all budgets.

The first funding budget for F3 is bimodal: 45 roads are funded at 40% budget, 31 roads only at 70%, and the remainder at intermediate levels. The early-funded roads correspond to Cluster2 (high NPV, high traffic), while the late-funded roads are mostly negative-NPV or low-return. This confirms that PCA-clustering effectively separates investable from non-investable roads, acting as a reliable screening tool.

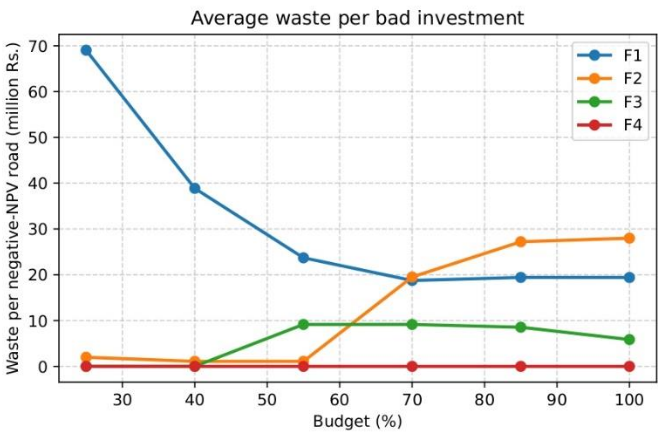

Figure 3. Average waste per negative-NPV road selected. F3 has zero waste until 55% budget; F1 wastes heavily

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5. CONCLUSION

This extended abstract builds on our earlier comparative study by introducing five novel analyses. VoI shows that upgrading from PCA-clustering to ILP is most beneficial at high budgets; at low budgets the gain is comparable to evaluation costs, making the decision context-dependent. MCA weight sensitivity confirms that a high weight on the benefit-cost ratio consistently improves accuracy. Waste per road reveals that F3 avoids costly bad investments until the budget exceeds 55%, by design. Cluster stability shows that F3 cleanly separates investable from non-investable roads. Moreover, F3 achieves higher population coverage than F4 while maintaining near-optimal accuracy and selecting almost exclusively positive-NPV roads.

While based on Sri Lankan data, the results are likely generalizable to other low-income countries with similar characteristics: rural road networks where (a) traffic data are sparse, (b) population density varies widely, and (c) economic returns are poorly correlated with physical condition.

The frameworks require only basic indicators (traffic counts, population served, rough cost estimates), which are available in most developing country road inventories. However, generalizability should be tested in at least one other country (e.g., Bangladesh, Tanzania) before global application. Condition-only IRI ranking should never be used—it wastes Rs.19–69M per bad road and has poor accuracy.

6. REFERENCES

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