Improvements to the IntiGIS Model Related to the Clustering of Consumers for Rural Electrification

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Abstract. Providing access to electricity in rural areas remains a challenge in many developing countries, where the lack of infrastructure, low population density, and high costs hinder the implementation of conventional electrification schemes. In this context, off grid solutions (microgrid and individual systems) have emerged as a promising solution, allowing the integration of local renewable energy resources and providing electricity to communities that are not connected to the main power grid. The IntiGIS model has been proposed as a tool to allow the evaluation and comparison of the various electrification technology options. However, some limitations and challenges have been identified in the original model, particularly related to the level of consumer aggregation and the distribution network layout. In this paper, we present improvements to the IntiGIS model related to the clustering of consumers for rural electrification, based on a modified agglomerative clustering algorithm and a set of performance metrics to form the clusters. We also present a comparison with the IntiGIS II version in a case study in Guamá, Santiago de Cuba to demonstrate the effectiveness of the proposed improvements. The results show that the modified IntiGIS model can generate clusters that meet the technical and economic requirements for microgrid and grid extensions systems, with better accuracy and efficiency than the original model. These improvements can contribute to the implementation of sustainable and reliable electricity access in rural areas, promoting social and economic development in these regions.

Keywords: Clustering Algorithm · Semisupervised Learning · IntiGIS · Geospatial Analysis · Rural Electrification · Energy Access · Sustainable Development

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1 Introduction

Access to electricity is a critical factor for socio-economic development, particularly in rural areas of developing countries. The lack of electricity in these areas is a significant obstacle for improving the living conditions of their inhabitants, who rely on traditional and inefficient energy sources. Therefore, rural electrification is a key strategy to reduce poverty, promote education, and enhance the overall quality of life [1].

However, rural electrification planning presents a number of challenges, including the high cost of extending the national grid to remote areas, the low population density typified by scattered settlements, and limited financial resources. That is why to make an informed decision, decision-makers rely on energy planning tools and models.

Among the literature studied, stand out the models for techno-economic and geospatial planning of large-scale rural electrification, also referred to as LCEM (Least-Cost Electrification Models) [2]. These models evaluate rural electrification alternatives based on Levelized Cost of Electricity (LCOE), making it possible to compare different electrification technologies without incurring the costs of physically building infrastructures, and by using geospatial planning, they also determine the location of each technology within the study area.

Examples of the aforementioned models are IntiGIS I [3], REM [4], ONSSET [5], RE2nAF [6], Mahapatra & Dasappa [7], Van Ruijven et al. [8], Dagnachew et al. [9], Sahai [10], Blechinger & Bertheau et al. [11, 12], Abdul-Salam & Phimiste [13, 14], Zeyringer et al. [15], Network Planner [16], Deichmann et al. [17], Levin and Thomas [18], GEOSIM[19] and Banks et al. [20].

One of the key inputs of these model is the map that represents the location of consumers[1] with their respective demands of energy. The consumer layer forms the foundation for all other geospatial data and dictates the spatial coverage of the analysis. There are several levels of consumer aggregation: individual consumers, communities, or cells. When a model operates at the level of villages or cells, the cells themselves are considered viable microgrids[2] or grid extensions. This fact reduces the computational complexity of the model by aggregating a large number of households into a smaller number of communities or grid cells. However, it will not be able to calculate the network layout that connects each consumer to the power source, whether it be the main grid or the generation site of the microgrid.

At the other hand, working with a high level of resolution like consumer level, requires an algorithm for clustering consumers with to identify areas with sufficient demand density to ensure the construction of a larger energy delivery system, such as a microgrid or the electrical network [2].

Clustering algorithms can provide insights into the underlying factors that contribute to electricity access disparities in rural areas, helping the decision-makers to identify the

[1] For the purposes of this investigation, the term "consumer" refers to a household or building that needs to be electrified.

[2] Also referred as mini-grids in literature, a microgrid refers to a small-scale electricity generation and distribution system that can operate independently or in conjunction with the main grid. It often includes renewable energy sources and energy storage and can serve as a reliable and cost-effective solution to provide electricity to remote or off-grid rural areas.

most suitable electrification solutions (isolated, microgrids, and grid extensions) for each group and allocate resources accordingly. The aforementioned models, except for REM, doesn't work at consumer level and therefore calculate LCOEs considering only the cost of connecting a cell or community with a single technology.

IntiGIS is a geospatial model that allows the evaluation and comparison of various technology options for electrifying rural areas.

This paper presents improvements to the IntiGIS model related to the clustering of consumers for rural electrification. Specifically, we focus on the RElect_MGEC algorithm, designed to create microgrid and grid extension clusters. The proposed improvements aim to enhance the accuracy and efficiency of the clustering process, resulting in more reliable and cost-effective electrification solutions.

The rest of the paper is organized as follows: Sect. 2 provides an overview of the IntiGIS Model an presents the proposed improvements to the model. Section 3 describes the results of the evaluation of the new clustering algorithm, including a comparison with the previous version. Finally, Sect. 4 concludes the paper and provides directions for future research.

2 IntiGIS Model

In Fig. 1, the evolution of IntiGIS is summarized (dates are approximate), where three stages can be seen: a first one corresponding to SolarGIS and SolarGIS II, a second one where versions of IntiGIS I and IntiGIS II emerged, and a third one that marks the starting point of the present investigation [21, 22] and upgrades made to the model. The current version of the tool, unlike the previous ones, was implemented in a QGIS free software environment. Highlights that allow the calculation and comparison of the LCOE of seven electrification alternatives: individual (based on photovoltaic, wind, diesel), microgrid (based on diesel, wind-diesel, photovoltaic-diesel), and grid connection. Additionally, it is possible to work at the consumer level, assigning different values of demand and power, and group them into microgrid and grid extensions clusters.

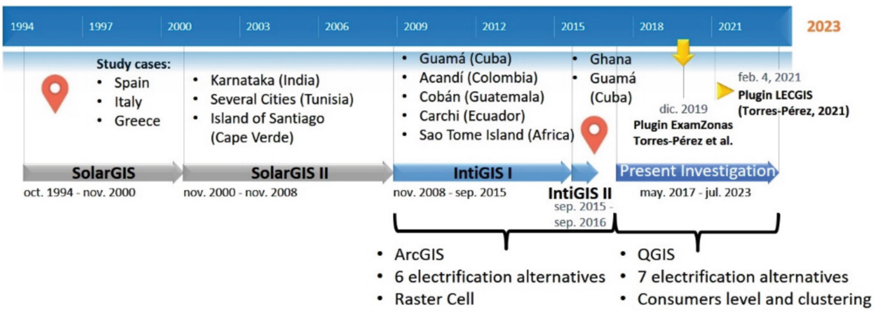

Fig. 1. Evolution of IntiGIS model.

The new version of the model consists of three components: 1. Territorial ordering analysis, 2. Geospatial clustering, and 3. Technical-economic analysis. Figure 2 shows an overview of the components with the interrelation and outputs of each one.

C1 carries out an analysis from the perspective of territorial ordering, with the aim of determining sensitive areas (non-viable) or barriers that should not be crossed by the layout of Low Voltage (LV) distribution lines. Some barriers may be associated with municipal limits or other administrative borders. These barriers can be used as input to C2 to support the clustering of consumers and allow the user to have different options to influence the way clusters are formed. C1 is based on the functionality to determine sensitive areas (barriers) of the ExamZonas plugin [22].

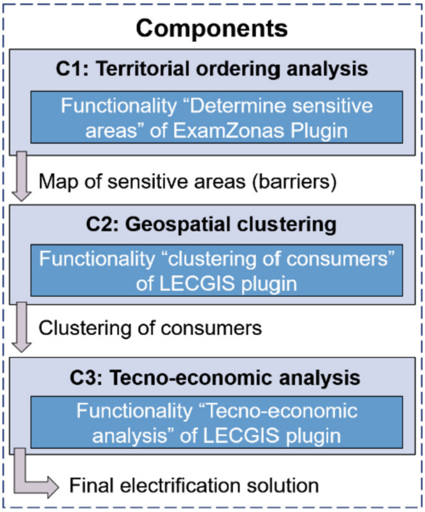

Fig. 2. Diagram components of the new version of IntiGIS model

The objective of C2 is to determine if there is sufficient demand density to guarantee the construction of a larger energy delivery system such as a microgrid or the electrical network [2]. This component will be described in more detail in the next section. The clustering solution generated by C2 is used as input to C3. This last component performs a techno-economic analysis of electrification alternatives using the "Techno-Economic Analysis" functionality of the LECGIS plugin described in [21].

2.1 The Proposed Geospatial Clustering Strategy

The proposed clustering strategy, named RElect_MGEC (Rural Electrification Microgrid and Grid Extension Clustering) fallows the approach of constrained clustering as a form of semisupervised learning, to clustering data while incorporating domain knowledge in the form of constraints. With this in mind the following metrics were stablished for the formation of the clusters[3]:

[3] The distribution infrastructure for microgrids and electrical grid extensions consists of a generation center and the branches connecting the center to a group of consumers. For this research, the term "cluster" refers to this distribution infrastructure with low-voltage lines.

- MinCons: Minimum number of consumers for a cluster to be considered valid.
- Radius: Search radius in which the MinCons must be found.
- MaxLongC: Denotes the maximum permissible distance between the generation center of the cluster and its associated branches that connect the consumers. This metric aims to restrict the energy losses that may occur during distribution. The generation center is assumed to be the location of the consumer with the smallest value of MaxLongC. Accordingly, the distance of a branch is determined by the sum of the widths of the path originating from the generation center till the leaf nodes.
- PotMax: Maximum power of the cluster (W). Obtained from the sum of the energy powers of the consumers in the cluster.

The algorithm RElect_MGEC consists of three phases: exploratory clustering, evaluation of potential clusters, and generating the results. The following are the steps to create the microgrid and grid extension (MGE) clusters:

1. In the phase one "exploratory clustering", the algorithm removes the consumers with PotMax greater than or equal to a specified value and runs the DBSCAN algorithm on the remaining consumers. The noise points that do not meet the minimum number of consumers required to form a cluster are labeled as isolated consumers.
2. In the phase two, each potential cluster resulting from the DBSCAN is evaluated by:
   a. Creating a Delaunay Triangulation (DT) that connects all the consumers.
   b. If a sensitive area or barrier map is provided, edges that intersect with these areas or are longer than the maximum distance from the generation center are removed.
   c. Build a weighted graph from the DT, where nodes are assigned weights based on the power of each consumer, while the edges have weights calculated as the ratio of their length and the sum of to the power of the consumers they connect.
   d. Computing the minimum spanning tree (MST)[4].
   e. If the tree is connected and satisfy the metrics MaxLongC, PotMax and MinCons it is added to the list of MGE clusters. Otherwise, for each connected component, the same evaluation is applied, and if the component satisfies the requirements, it is also added to the list of MGE clusters.
   f. If the clusters do not satisfy these conditions, the RElect-BUC algorithm (see **Algorithm 1**) is used to further cluster the consumers.
3. Finally, in the third phase, the algorithm generates the results by creating shapefiles for the resulting clustering of consumers and LV distribution lines for each cluster.

The density-based spatial clustering algorithm presented by authors [23] shares some similarities with the RElect_MGEC algorithm. Their approach utilized a DT with edge length constraints to generate a network of connected vertices, which was subsequently analyzed using a modified density-based strategy to identify spatial clusters.

RElect-BUC algorithm is based on graph theory to perform agglomerative clustering that ensures the obtained clusters meet the established metrics. First, all the edges of the graph are sorted according to their weight from smallest to largest. Initially, all edges are considered inactive. In this sense, the edges of the graph correspond to the clustering

[4] A MST is the set of connections between customers so that all customers are connected directly or through other customers and the sum of the lengths of the connections are minimized. To create the MST, we use the minimum_spanning_tree function in the NetworkX library.

decisions. An edge can be activated to merge the consumers on both sides of the edge into a single cluster, or remain inactive to leave them in separate clusters. This decision is based on whether they meet the previously defined metrics. Finally, once all the edges have been considered, the series of interconnected consumers that meet the metrics will be the clusters of microgrids and network extensions.

Algorithm 1. RElect_BUC

```
Input: T, a weighted connected graph
Input: MaxLongC, the maximum length from the generation center
Input: PotMax, the maximum power of a cluster
Input: MinCons, the minimum number of consumers for a cluster
Output: Lr, a resulting list of microgrid and network exten-
sion clusters
Sort the edges of T by their weight
Create an empty graph, T'
For each edge i in T do
// The nodes that connect the edge will be automatically added
if they are not already in the graph T'
    Add edge i to the graph T'
    For each connected component c in T' do
      If edge i exists in c then
        If graph_MaxLongC(c) >= MaxLongC or graph_to-
tal_power(c) >= PotMax then
          Remove edge i from graph T'
        End if
      End if
    End for
End for
For each connected component cn in T' do
  If number_of_nodes(cn) >= MinCons then
    Add cn a Lr
  End if
End for
Return Lr
```

3 Application and Results Analysis

To evaluate the influence of the improvements introduced to the model as part of the geospatial clustering component II, it was proposed a comparison with the case study conducted by [24] in the Guamá municipality. The maps from the original case study can be accessed through the geoportal: http://arcg.is/2ffrzAY. The same technical-economic parameters presented in Annex V of the thesis were employed, but with the consumers grouped using the proposed clustering strategy, in contrast to the original analysis that was performed at the raster cell level to represent consumers. This approach will also allow for a comparison between the current version and the IntiGIS II version.

For the application of the clustering proposal, the next experiments were design:

- E1: execution of RElect_MGEC with the parameters MinCons = 5, Radius = 200 m, MaxLongC = 1000 m, and PotMax = 46200W.
- E2: execution of RElect_MGEC, with Radius = 250 m and the same rest parameters.
- E3: direct application of RElect_BUC without using the DBSCAN algorithm in Phase 1. This approach began by calculating the DT that connects all consumers in the study area. With the input parameters MinCons = 5, MaxLongC = 1000 m, and PotMax = 46200 W.

The "Clustering of Consumers" functionality (C2 in Fig. 2), was implemented using the QGIS API functions and the NetworkX library [25]. It is part of the upgrades made to the LECGIS plugin described in [21], which was also updated to work with version 3.x of QGIS.

To establish a reference value for PotMax, we analyzed the demand raster used as input for IntiGIS II in search of the highest cell density. The maximum number of households per cell found was 14, and considering that the contracted power per household is Ph = 3300 W, the resulting aggregated power would be 46200 W. The value of MaxLongC was recommended by energy specialist we consulted. The Radius was set between 200 and 250 m, considering the raster resolution of the consumers layer in the original study, which was 400 m. Also, with the purpose of facilitating the comparison between the two different versions of IntiGIS, we did not use the barriers layer, to recreate similar conditions to the original case. Figure 3 displays the layer used as input for the experiments E1–E3, with the 3535 consumers located in the study area.

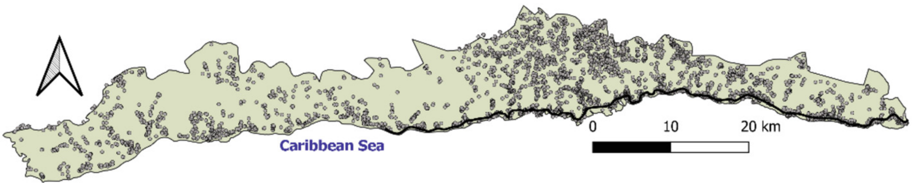

Fig. 3. Layer of consumers from the Guamá municipality

The result from each experiment (E1, E2 and E3) using the clustering of consumer (C2 in Fig. 2) is inputted into C3 to calculate the LCOE of the same electrification alternatives as in the original Guamá case study. The electrification alternatives considered include individual (based on photovoltaic, wind, diesel), microgrid (based on diesel, wind-diesel), and grid connection. The experiments were conducted on a workstation with Intel(R) Core(TM) i7-8750H CPU @ 2.20GHz, NVIDIA GeForce GTX 1050 GPU with 4GB of DRAM and 24 GB RAM. The comparison of results obtained after the execution of the three clustering experiments over the map of consumers in Guamá municipality is presented in Table 1.

Table 1. Results comparison of clustering proposal experiments

Experiment	Average of clusters size				Total Execution Time
	Total of consumers	MaxLongC (m)	PotMax (W)	Total LV lines (m)	
E1	9	375.15	26154.7	755.34	35 s, 394 ms
E2	8	430.284	27053.6	860.51	51 s, 382 ms
E3	9	678.669	29563.7	1350.66	4 min, 11 s

Note: PotMax value match with the total power of the consumers in the cluster.

In Table 2, the comparison of results for the entire study area of Guamá municipality is shown. By observing the fourth column, it is noted that the number of cells in IntiGIS II with 1410 is much higher than those generated by the proposed clustering strategies. This is due to the fact that in the original case study, the layer of 3535 consumers was rasterized to a resolution of 500 m.

Table 2. Comparison of LECGIS and IntiGIS II tools for Guamá municipality study area

Tool	Spatial Resolution	Clustering variant	Nº of clusters or cells/Tot. Consumers	Total LV lines (m)	Nº of consumers or cells for recommended Technology		Total LCOE (cts. €/kWh)
					Photovoltaics	Grid	
IntiGIS II	Cells of 500 m	-	1410/3535	275975	1275*	291*	126976
LECGIS	Consumers	E1	148/1173	111792	3004	531	308647
		E2	207/1697	178127	2851	684	287289
		E3	339/3037	457873	2641	894	287294

* Value obtained from a raster layer of 400 m resolution from a total of 1566 cells.

Figure 4 illustrates the contrast between representing consumers as point vectors versus raster cells in a grid format, in a portion of the study area. The image displays LV line length values (in light blue) for each pixel, and highlights three clusters in green, blue, and pink, respectively. The black line represents the total line length value computed from the MST. IntiGIS II divided the consumers contained in the three clusters into 5 cells, resulting in smaller partitions that require shorter line lengths. However, these partitions are impractical from an energy point of view.

Cell number 6 (counting from left to right and top to bottom) has only one consumer (white point) and a value of 316.38 m. For IntiGIS II, this cell represents a viable micro-grid or grid extension, and therefore it will calculate all the centralized electrification alternatives for that cell, even though designing a system with those characteristics is impractical. On the other hand, the clustering algorithm has labeled that consumer as isolated and has therefore discarded it for the calculation of centralized alternatives. Lastly, regarding to the total LV lines E1 and E2 yielded lower count than IntiGIS II.

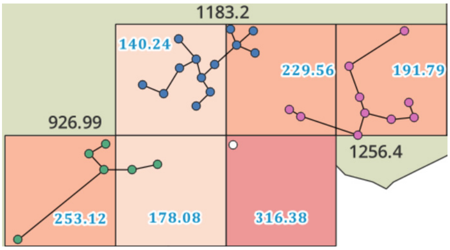

Fig. 4. Overlap of raster map of low voltage line and a clustering of consumer's layers (Color figure online)

Additionally, one of the advantages of working at the consumer level in the new version of the tool is that it is not necessary to transform vector shapes to raster format.

The comparison of the total LCOE cost was difficult because inconsistencies were found in the resolution of the input (500 m) and output (400 m) rasters, provided by the Geographic Information Technologies and Renewable Energies (gTIGER) units from CIEMAT. It was found that the layers sent by gTIGER correspond to those in the thesis document [24]. Since we did not have access to an installation of IntiGIS II, it was not possible to run the tool and determine whether the discrepancies we observed were due to a software malfunction or to human error on the part of the thesis author, who may have selected inappropriate output layers when conducted different experiments. In addition to the difference in raster resolution, it was found that the output raster is missing pixels in areas where consumers exist in the vector map.

It can be observed in the total cost column of Table 2 that IntiGIS II has lower values, but this may be due to the missing pixels. Furthermore, due to the fact that the IntiGIS II program automatically assigns grid connection as the most profitable option for settlements located less than 800 m from the medium voltage line (visualized in Fig. 5), these values are not calculated and therefore are not available in the LCOE results maps.

Among the experiments conducted using the new version, E2 demonstrated the lowest total cost, followed closely by E3. Figures 5, 6, 7 and 8 display maps showing the spatial distribution of the final electrification solutions obtained. To better visualize the differences between the solutions, a zoomed-in view of the existing electrical network area (represented by a solid black line) is displayed, as this is where the differences are concentrated. Each map displays consumers or cells in red to indicate the recommendation of implementing individual photovoltaic systems, while those in green indicate the recommendation of extending the electrical grid. For the remaining consumers not shown in the zoomed-in region, the recommended system was individual photovoltaic in all cases.

Figures 6, 7 and 8 correspond to the solutions that employed the clustering of consumers, and demonstrate that it is possible to recommend individual systems for places located less than 800 m from the electrical network. This finding provides valuable insights for energy distribution and access in the study area, as it suggests that clustering can be an effective strategy for improving the efficiency and cost-effectiveness of electrification efforts.

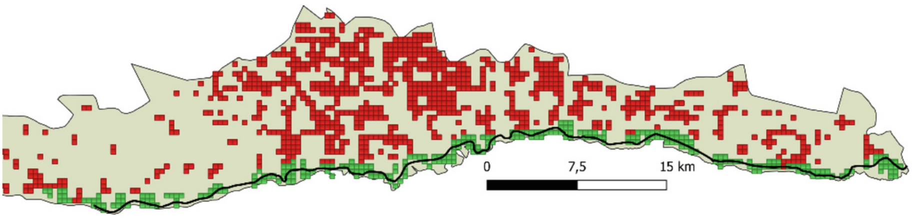

Fig. 5. Zoom in to the final electrification solution with IntiGIS II

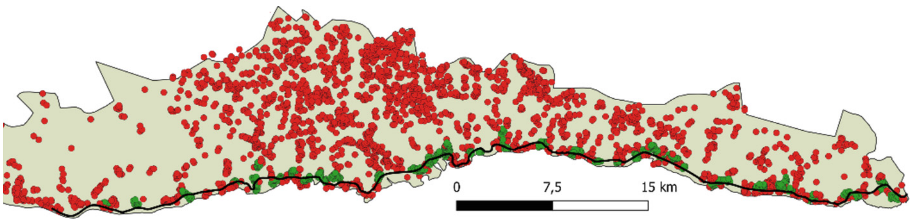

Fig. 6. Zoom in to the final electrification solution using E1 clustering of consumers

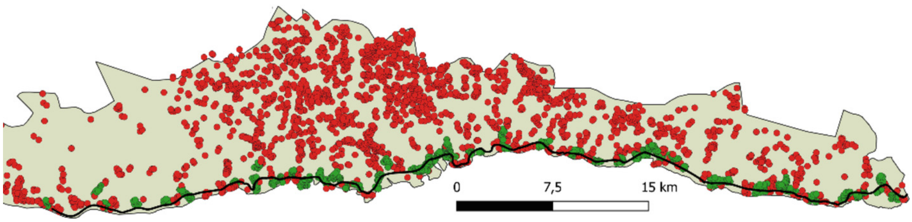

Fig. 7. Zoom in to the final electrification solution using E2 clustering of consumers

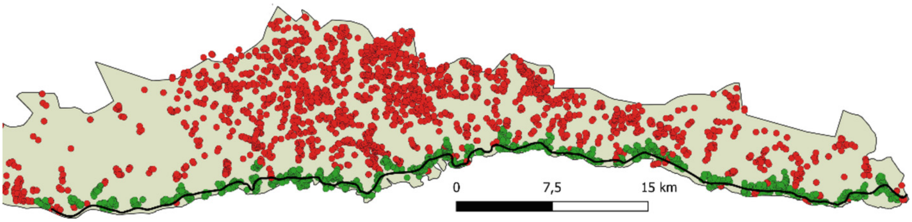

Fig. 8. Zoom in to the final electrification solution using E3 clustering of consumers

4 Conclusions

By considering the unique features of rural areas, clustering algorithms have the potential to transform the planning and implementation of rural electrification projects, leading to more sustainable and equitable outcomes. The IntiGIS model has been proposed as a tool to support the planning and design of microgrid systems, using a geospatial clustering approach to group consumers and optimize the distribution network.

In conclusion, the proposed improvements to the IntiGIS model have shown promising results in terms of accurately clustering consumers for rural electrification. The integration of geospatial clustering techniques, such as DBSCAN and graph partitioning, has allowed for a more granular analysis of consumers and their connectivity, leading to the identification of microgrid and grid extension clusters that meet the technical and economic metrics established for the project. Overall, the consumer-level data enable a more detailed analysis and prove effectiveness of the geospatial clustering approach in rural electrification planning.

The results obtained from applying the RElect_MGEC algorithm to a case study in the Guamá municipality demonstrate the effectiveness of the proposed approach in comparison to the IntiGIS model version based on raster. Further research can be conducted to explore the applicability of the proposed improvements to other rural electrification projects and to evaluate their performance under different conditions and contexts. Overall, the proposed improvements to the IntiGIS model contributes to the field of rural electrification and pattern recognition, with the potential to improve access to electricity for underserved communities around the world.

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