Integrative Spatial Modeling for Ecosystem Management: A Case Study in Maasai Mara

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Abstract. This study presents a generalized approach to wildlife management by introducing two adaptable models suitable for environments with varying data availability. Utilizing a Gridded Species Distribution Model and a Min-Max Model that incorporates the Simplified Floyd-Warshall Algorithm, we demonstrate a methodology capable of mapping species distributions and enhancing monitoring efficiency in habitat-rich reserves. The Gridded Model, through Optimized Hot Spot Analysis, successfully delineates critical habitats, and the Min-Max Model efficiently places monitoring stations, considering Kenya's technological landscape and data collection capabilities. Collectively, these models underpin a versatile and strategic framework, reinforcing conservation efforts in the Maasai Mara and suggesting potential for application in other contexts where similar ecological and resource challenges exist.

Keywords: Gridded Species Distribution Model, Wildlife Conservation, Min-Max Floyd-Warshall Algorithm.

1. Introduction

Kenya is known for its rich wildlife resources. For example, covering 1,672 square kilometers, the Masai Mara is one of the world's top tourist attractions and Kenya's premier protected area.[1] Kenya’s well-developed tourism has provided the impetus for its economic growth. Personal and business tourism together account for 17% of Kenya's total services exports[2].

Kenya is known for its rich wildlife resources, but it is also often accompanied by conflicts between humans and animals [3]. In recognition of these challenges and the critical role the Maasai Mara plays in global conservation efforts, our study specifically targets this reserve. The aim is to apply and evaluate innovative modeling approaches that can address the Reserve's unique conservation challenges. We introduce two pioneering models: the Gridded Species Distribution Model and the Min-Max Model based on the Simplified Floyd-Warshall Algorithm. These tools are meticulously designed to bolster the management strategies within the Maasai Mara.

The Gridded Species Distribution Model employs a grid-based approach to systematically map and analyze wildlife distribution, aiding in the identification of critical habitats for targeted conservation efforts. Concurrently, the Min-Max Model optimizes the deployment of monitoring stations around these habitats, ensuring effective surveillance and conservation resource allocation. Together, these models form a cohesive strategy for sustainable wildlife management and illustrate our commitment to enhancing the Reserve's stewardship.

By integrating these models, we provide a novel perspective on managing and conserving the Maasai Mara’s diverse ecosystems. Our approach demonstrates how advanced spatial analysis can be a game-changer in preserving wildlife while supporting sustainable tourism and economic growth. This research not only makes a significant contribution to the ecological stewardship of the Maasai Mara but also serves as a template for conservation initiatives in similar ecosystems around the world.

As we delve deeper into the methodology and findings, we aim to demonstrate how these models can be instrumental in formulating innovative conservation strategies, ensuring that the Maasai Mara remains a vibrant and thriving sanctuary for future generations.

2. Literature Review

Previous studies on game reserves are instructive in addressing the above problems. We first reviewed "Human-wildlife conflicts in a Nepalese protected area: conservation challenges, mitigation strategies, and policy implications," which highlights the importance of "inclusiveness" in the Nepalese region, emphasizing the need to find solutions that balance protection with the livelihoods of residents[4], thus drawing a blueprint for our plan.

In Meng et al.'s study of the spatiotemporal variation and the coordination between humans and grassland ecosystems, they analyze a gridded grazing dataset to assess the changing dynamics and interactions. [5], they place different areas within the reserves as cells in a grid system and divide them into different protection categories. Kolluru et al. developed a high-resolution gridded livestock density (LSKD) database for Kazakhstan, covering the period from 2000 to 2019, to address the need for detailed spatial and temporal livestock data in dryland Asia. [6], This inspires us to place the regions of the Maasai Mara in a grid system and to classify them according to their relative position.

3. Methodology

3.1. Assumptions and Justifications

To streamline the problem, we introduce several assumptions with their justifications. Firstly, we assume unrestricted movement and adopt the Manhattan distance over the straight-line distance. This is supported by the observation of the Maasai Mara's vast plains and numerous passable shallows and junctions in the river, as indicated by satellite imagery from Google Maps. Given the terrain is divided into a grid system, the Manhattan distance becomes a reasonable approximation for short distances within this wide area. Secondly, we consider only buffalo, elephant, giraffe, wildebeest, and zebra as representative of all wildlife, based on an analysis excluding birds for their mobility and many mammal species for their scarcity or limited observations. These chosen species are deemed representative after extensive review. Figure 1 will show a photo of the rivers in Maasai Mara which comes from Google Maps.

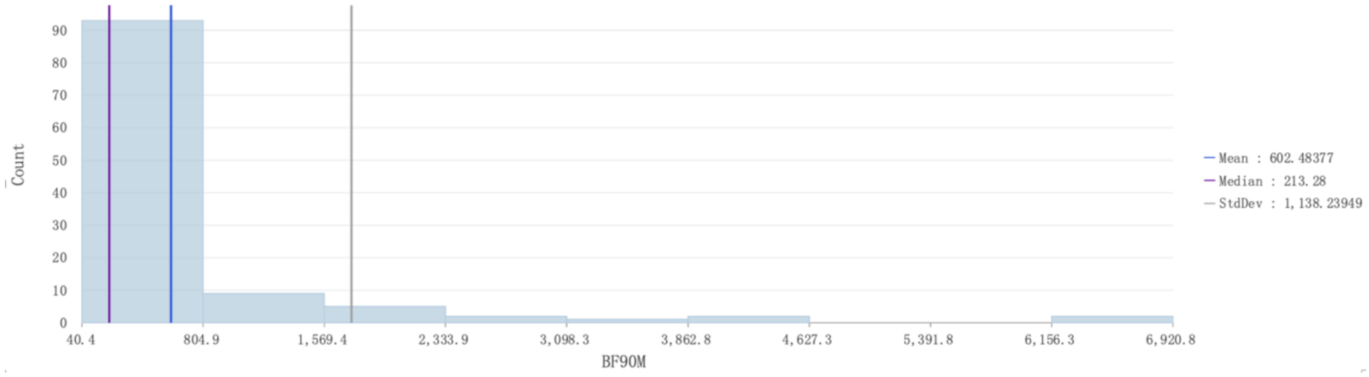
Figure1. A Sample Satellite Photo of the Rivers in the Maasai Mara

Due to the minimal difference between Manhattan distance and straight-line distance within the small and uniform square grid divisions of the Maasai Mara, the former can adequately substitute for the latter, ensuring the model's validity. Furthermore, after referencing the work of Rezania and Febriyanti[7], we also employed the Haversine Formula, as it can calculate the distance between any two points on the Earth.

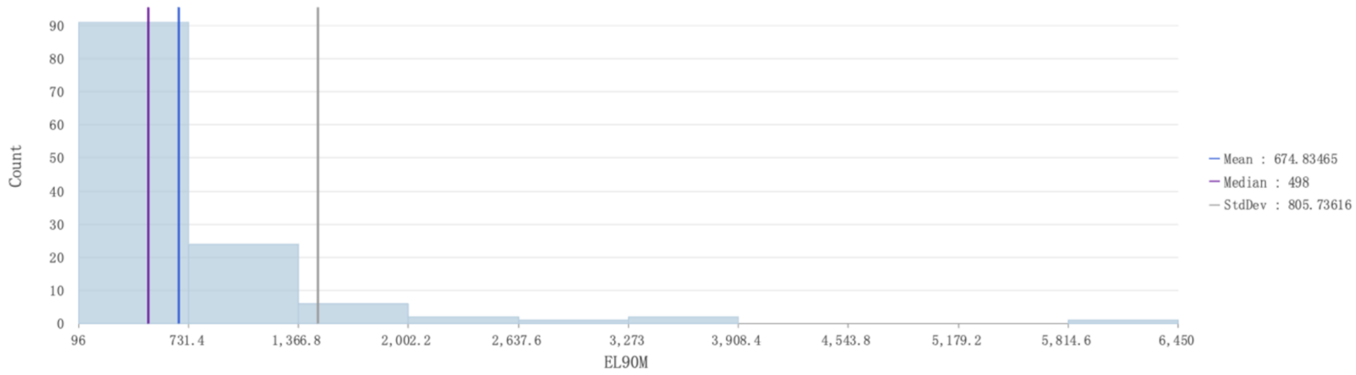
Lastly, we assume the data collected from authoritative sources such as Maasai Mara National Park and ArcGIS databases is reliable and that the long-term trends observed will remain consistent in the future. This confidence stems from the data's authoritative origins and its coverage over an extended timeframe, supporting the study's assumptions.

3.2. Model Development and Data Acquisition

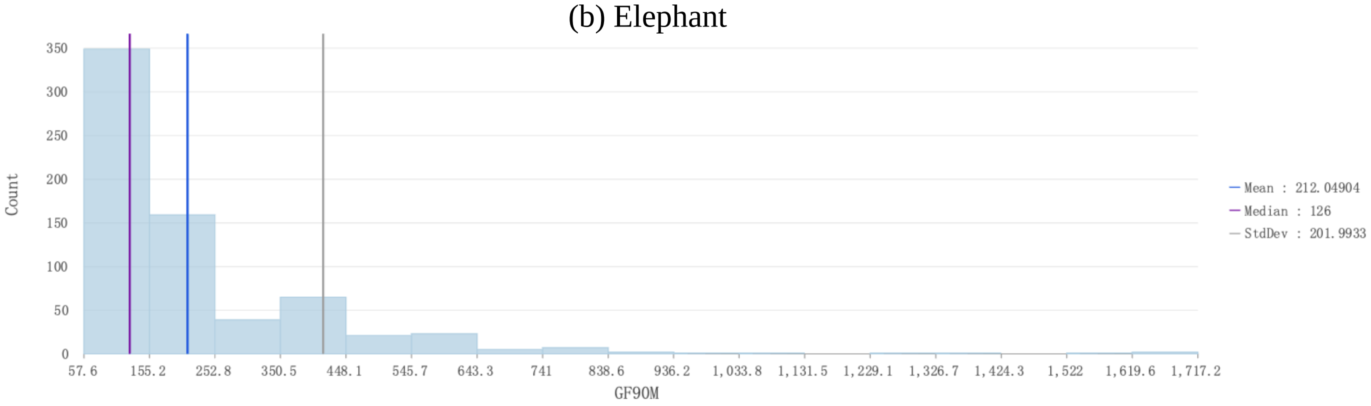
Prior to constructing our models, we conducted a detailed statistical analysis of animal distributions, as described in below. We segmented the Maasai Mara into grids and tallied the species present in each to generate the histograms depicted in Figure 2. These histograms illustrate the frequency distributions of buffalo, elephants, giraffes, wildebeests, zebras, and other mammals across different grid cells. Our analysis indicates that the distributions of buffalo, elephants, and giraffes across the grid cells exhibit varied levels of population density, contrary to the previously suggested non-significant variation.



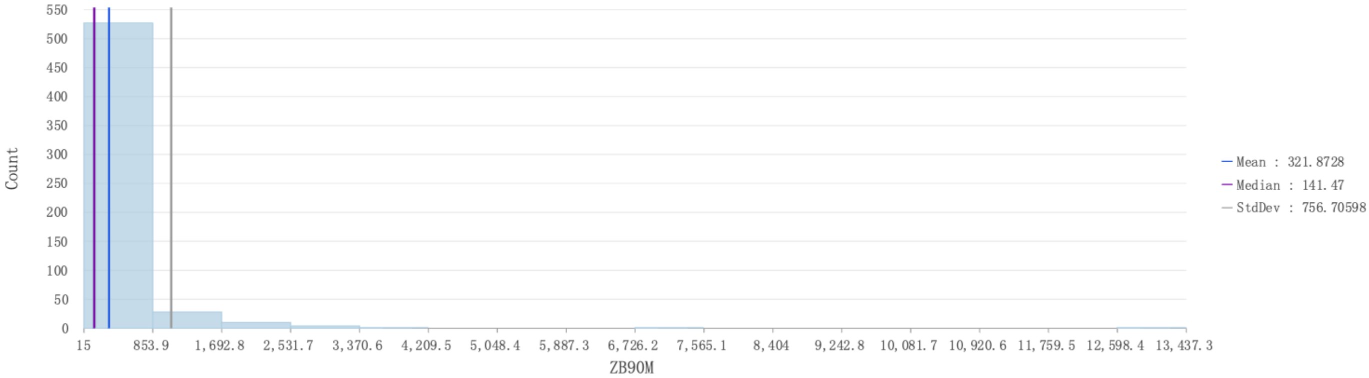
(a) Buffalo



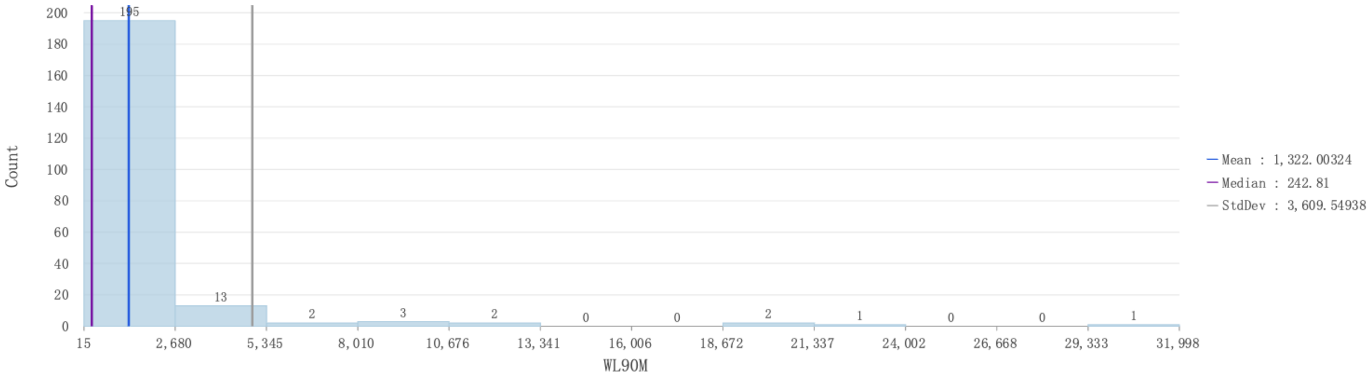
(b) Elephant



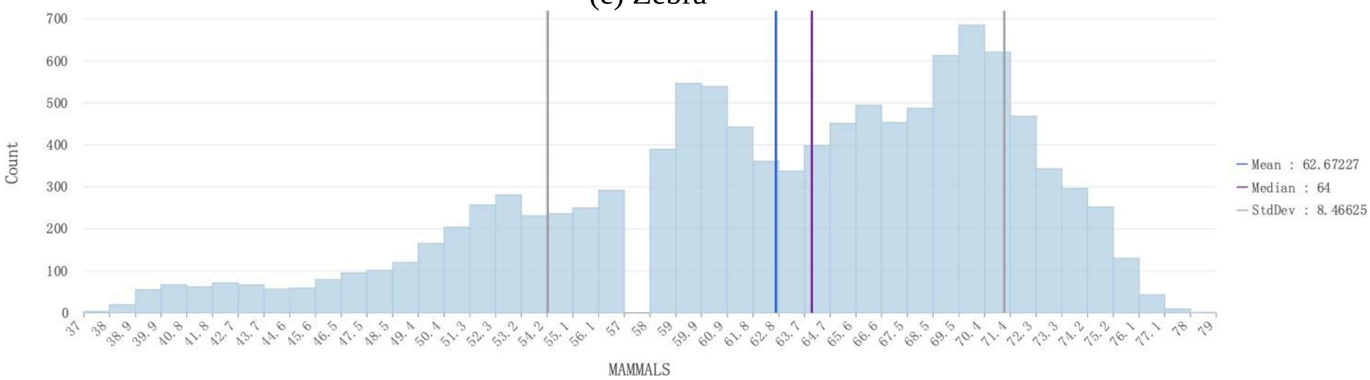
(c) Giraffe



(d) Wildebeest



(e) Zebra



(f) The Mammals

Figure 2: Histogram of Wildlife Distribution

To develop the gridded species distribution model, our approach was to divide the Maasai Mara protected area into grid overlays to allow for a systematic analysis of species distribution across the landscape. In implementing the gridded species distribution model, the spatial analysis software ArcMap was used to optimize the hotspot analysis and divide the Maasai Mara area into grids at a resolution of 1 km × 1 km, and each grid cell was analyzed for species presence, environmental conditions, and human activities, to determine the density and distribution pattern of the wildlife and to facilitate detailed species distribution analysis, and ultimately to obtain a statistically significant Maasai Mara species distribution heat map.

For better classification of blocks, we first need to process the wildlife statistics to derive the biodense areas of the Maasai Mara. We were inspired to use ArcGIS after referring to the article "Map Visualization in ArcGIS and MapInfo"[9]. Furthermore, we employed "Optimized Hot Spot Analysis" to address the problem.

Optimized Hot Spot Analysis allows us to calculate a statistically significant heat map of species distribution by Getis-Ord Gi* from the species statistics we input. The following equations show how to calculate $G_{i,j}^{*}$:

$$G_{i,j}^{*} = \frac{\sum_{j=1}^{n} v_j - V\sum_{j=1}^{n} w_{i,j}}{S\sqrt{\frac{\left[n\sum_{j=1}^{n} w_{i,j}^{2} - (\sum_{j=1}^{n} w_{i,j})^2\right]}{n-1}}} \tag{1}$$

Were,

$$V = \frac{\sum_{j=1}^{n} v_j}{n} \tag{2}$$

$$S = \sqrt{\frac{\sum_{j=1}^{n} v_j^2}{n} - V^2} \tag{3}$$

$G_{i,j}^{*}$	z-score (standard deviation) of cell i and specie j
$w_{i,j}$	the spatial weight between cell i and specie j
v_j	the attribute value for specie j
n	the total number of cells

We input the species distribution data into the model and the species distribution heat map can be plotted by the value $G_{i,j}^{*}$ obtained. The rationale behind this is that for a statistically significant, if $G_{i,j}^{*}$ is positive, the larger the $G_{i,j}^{*}$, the more intense the clustering of hot spots; conversely, if $G_{i,j}^{*}$ is negative, the smaller the $G_{i,j}^{*}$, the more intense the clustering of cold spots.

For each species we study, we obtain a corresponding heat map of the distribution. We notice that $G_{i,j}^{*}$ is always positive. To be able to integrate all the heat maps into one, we innovatively use the algorithm showed in Figure 3 to draw the Species Distribution Heat Map.

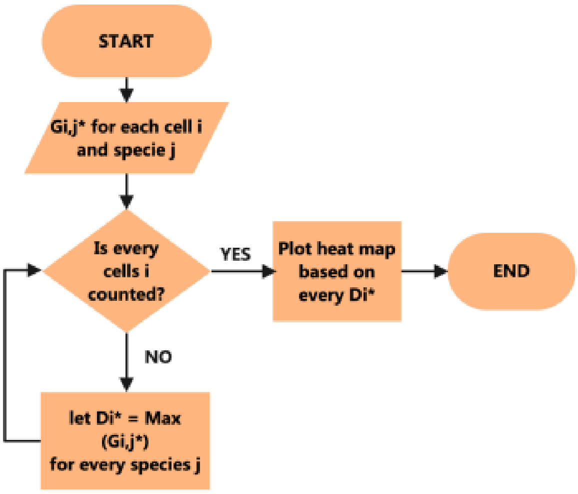


Figure 3: Algorithm for the Heat Map

For our data collection, the data comes from the Kenya Wildlife Service and remotely sensed satellite imagery, which provide comprehensive coverage of the terrain and wildlife patterns, from which we can calculate Getis-Ord-Gi* statistics to generate a heat map that accurately depicts the areas where important wildlife congregates in the Maasai Mara to determine the intensity of the species' presence, which in turn guides the core and fringe habitat delineation."

Marginal areas identified by the gridded species distribution model were input into the Min-Max model using a simplified Floyd-Warshall algorithm to efficiently optimize the layout of monitoring stations. The model uses transformed geographic coordinates to create a distance metric for optimal monitoring station locations using Haversine's formula. The aim is to minimize the maximum distance between monitoring stations and key habitat areas, thus ensuring effective wildlife monitoring and conservation efforts.

3.3. Algorithm Application and Optimization Techniques

For the min-max model, we implemented a simplified Floyd-Warshall algorithm to determine the optimal location of monitoring stations. The algorithm was tailored to the unique geographic and ecological characteristics of the Maasai Mara, and due to the grid approach of the model, it utilized the Manhattan distance metric. And it uses a conversion of geographic coordinates to a distance metric using Haversine's formula and adjusts the Manhattan distance metric for the gridded environment of the Maasai Mara. This adjustment allowed us to address computational complexity while maintaining the accuracy of the distance measure in the gridded landscape.

We learn efficient distance calculations and matrix operations using Python by studying "Python for Data Analysis" written by McKinney and others [10]. Custom-developed Python scripts iteratively tested various configurations of monitoring stations, aiming to minimize the maximum distance from any point in the edge area to the nearest monitoring station. This iterative process ensured that the final solution provided the most effective coverage with the minimum number of monitoring stations, balancing conservation needs and resource constraints.

We determined the optimal number and location of monitoring stations by considering the tradeoffs between monitoring coverage and the resources available to establish monitoring stations. This process included the development of a pseudo-code framework (shown in Figure 4) to facilitate the evaluation of various monitoring station placement scenarios to ensure that the final configuration provided the greatest possible coverage of edge habitat with the least number of monitoring stations.

Algorithm 1: Min-Max Model based on simplified Floyd-Warshall Algorithm

Data: ordinates of monitoring stations (x, y), number of monitoring stations k, number of edge areas n, a 2-dimensional array of the digitized grid system map

Result: optimal locations of monitoring stations loc, the minimum of the maximum distance $distF$

```
d_min ← ∞;
α stores the coordinates of edge areas;
C stores the number of combinations;
for i in 1 : α.length do
    for j in 1 : k do
        compute d_{i,j};
    end
    max = 0;
    for y in 0 : map.length do
        for x in 0 : map[y].length do
            temp = Min(d_{x,y});
            if d_max < d_{x,y} then
                d_max = d_{x,y};
            end
        end
        if d_max < d_min then
            d_min = d_max;
            distF = Min(d_{i,j});
            loc stores the locations of monitoring stations which provides the
              optimal solution;
        end
    end
end
```

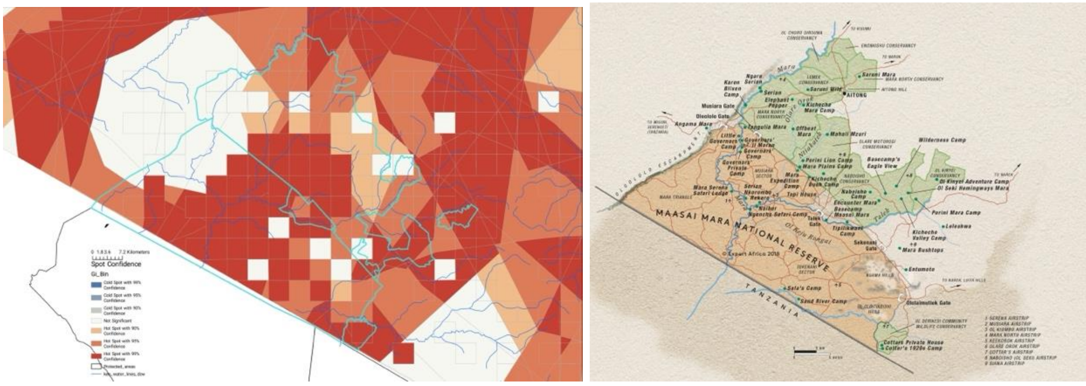
Figure 4: Pseudo-code Framework of Min-Max Model

In applying the Min-Max model, we used a simplified Floyd-Warshall algorithm to calculate the shortest path for placing monitoring stations within a defined edge area. The algorithm was tailored to the unique geographic and ecological characteristics of the Maasai Mara, and due to the model's grid approach, it utilizes the Manhattan distance metric. This modification allowed us to address computational complexity while maintaining the accuracy of distance measurements in the gridded landscape.

We determined the optimal number and location of monitoring stations by considering the trade-off between monitoring coverage and the resources available to establish them. This process included the development of a pseudo-code framework to facilitate the evaluation of various monitoring station placement scenarios to ensure that the final configuration provided the greatest possible coverage of edge habitat with the least number of monitoring stations.

4. Results

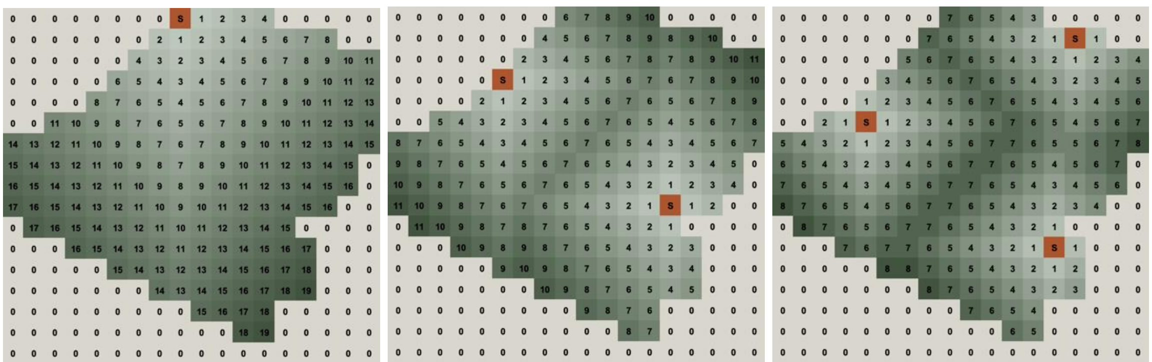
Through the new species distribution model, the following six species weight distribution maps were obtained, showing in Figure 5(a). We take out the location of the Gi maximum and plan it into a completely new animal habitat area. 26/150 or 20% more area for the protected areas than the original protected areas with high hotspot fauna. At the same time, we have reduced the distribution of reserves in areas where the fauna is not clearly distributed. Although our entire core area is 20% smaller than the game preserve area, we have covered more animals and increased the conservation rate. We have also set up guard towers, which in our hypothesis not only allow for the rapid dispatch of medical teams but also serve as a safeguard against poaching.



(a) Heat Map. (b) Actual Map

Figure 5: Species Distribution Heat Map

For different numbers of monitoring stations, we investigate the optimal location to set them and calculate the longest Manhattan distance from the monitoring station to the core areas. By taking different values for the number of monitoring stations, we find that the longest Manhattan distance is 8 units when the number of monitoring stations is greater than or equal to 4, indicating that continuing to increase the number of monitoring stations will only create redundancy. When 1, 2, and 3 monitoring stations are set, the longest Manhattan distance is 19, 11, and 8 units, respectively. To make the longest Manhattan distance as small as possible, we consider setting 3 monitoring stations as the optimal strategy. For the case of 1, 2, and 3 monitoring stations, the visualized scheme is shown in Figure 6.



(a) 1 Station (b) 2 Stations (c) 3 Stations (Optimal)

Figure 6: Locations of Monitoring Stations*

*S: Locations of Monitoring Stations; 0: Non-core areas; Other numbers indicate the Manhattan Distance.

4.1. Analysis of Model Outputs

The output of the gridded species distribution model was analyzed through species distribution heat maps. These heat maps revealed areas of high species concentration, effectively distinguishing between core and edge habitats. When juxtaposed with satellite imagery and observational data, the heat maps correlate closely with areas known to be wildlife-rich, validating the accuracy of the model in representing actual species distributions.

In implementing the min-max model, we used a simplified Floyd-Warshall algorithm to examine the strategic placement of monitoring stations in marginal areas. Using this approach, we determined that establishing three monitoring stations would provide the most effective coverage. This was confirmed by the heat maps generated by the model, in which the proposed locations of the monitoring stations are close to the marginal areas to be monitored, as shown in the visualization scheme provided in Figure, which provides strong support for animal protection.

4.2. Results and Implications for Conservation Efforts

This study utilizes advanced modeling techniques and GIS tools, as referenced in "Mastering ArcGIS Pro," to enhance conservation efforts in the Maasai Mara [11]. The integration of spatial analysis into these efforts provides a solid foundation for habitat and species management. The gridded species distribution models offer insights into the spatial dynamics of species, crucial for crafting targeted conservation strategies. Identifying core areas suggests minimizing human activities to maintain ecological integrity. The results from the min-max modeling underpin the establishment of a monitoring network to ensure comprehensive monitoring of wildlife activity and potential poaching. The optimal network layout enables comprehensive coverage and efficient resource allocation, critical for rapid response and management in protected areas.

5. Conclusion

The study advances a more precise approach to managing the complex relationship between wildlife conservation and human activities in the Maasai Mara. Both the gridded species distribution model and the minimum-maximum Floyd-Warshall model demonstrate strong predictive accuracy and operational efficiency, making them practically applicable for wildlife management. By incorporating these models into decision-making, the conservation management in the Maasai Mara can be significantly strengthened, and similar strategies could be applied to other protected areas with comparable challenges. Future research should focus on integrating these models with real-time monitoring techniques like satellite tracking and drone surveillance to enhance dynamic management of wildlife reserves. Further validation of the adaptability of these models in nature reserves with different ecological characteristics and anthropogenic impacts will help understand their scalability and versatility in various conservation scenarios.

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