Site Planning for a Network of Government-operated Weather Stations in the Dominican Republic Using Zonal Statistics from Geospatial Sources, Multi-Criteria Decision-Making, and Neighborhood Analysis

This is a non-peer-reviewed preprint submitted to EarthArXiv and has not yet been submitted to any journal.

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Abstract

Many weather station networks lack sufficient representativeness, and their station density is often inadequate to capture spatial and climatic variability effectively. Optimal site selection is therefore essential to enhance spatial coverage and improve data quality. This study proposes a methodology for identifying optimal sites for a meteorological station network in the Dominican Republic, utilizing a multi-criteria decision-making framework based on the Analytic Hierarchy Process (AHP) and neighborhood analysis. Using the H3 library as a spatial indexing tool, zonal statistics were derived from geospatial variables, including seasonality, habitat heterogeneity, proximity to water bodies, slope, solar radiation, and elevation. Expert-defined weights were assigned to each variable based on their relative importance. Areas with high topographic and climatic variability were prioritized to maximize spatial representativeness. Results highlight thermal and precipitation seasonality, elevation, and solar radiation as the most influential variables, emphasizing the need to collect data in elevated areas with marked seasonality. Sites were evenly distributed across three density scenarios, ensuring robust climatic and topographic coverage while avoiding redundancy through proximity constraints to existing stations. The proposed network would provide essential data for meteorological and climatic research in the region. Future studies should assess the accessibility and feasibility of the selected sites and incorporate additional environmental variables into the framework.

Keywords Weather stations networks · Optimal site selection · Spatial coverage · Multi-criteria decision-making · AHP

1 Introduction

Weather stations (WS) are essential for collecting accurate and up-to-date data on weather and climate in specific regions. The applications of the data collected by WS extend beyond meteorology and climatology, finding widespread use in fields such as engineering, agriculture, urban planning, and geography, among others (Chung et al., 2018; Marchi et al., 2019; Wilgen et al., 2016; World Meteorological Organization (WMO) & The International Association of Hydrological Sciences, 1976). The data provided by these stations are instrumental in predicting extreme weather events, such as tropical storms, hurricanes, tornadoes, and droughts, enabling communities to prepare and respond effectively. Furthermore, WS data underpin numerous scientific studies on climate and climate change, helping to better understand atmospheric dynamics and their impacts on the planet, ultimately contributing to more informed and effective planning strategies (World Meteorological Organization (WMO), 1996, 2017a, 2017b).

A robust WS network is crucial for making informed decisions across various domains and is fundamental for the well-being and safety of communities and the environment. Planning an adequate WS network is essential for effective land management. Previous studies, including those conducted in the Dominican Republic, reveal significant gaps in WS coverage in key areas and highlight the uneven spatial distribution and low density of existing networks, which likely affect the accuracy of collected data (Frei, 2003; Programa Mundial de Alimentos (PMA), 2019; Rojas Briceño et al., 2021; Theochari et al., 2021).

Many countries have evaluated the design of their WS networks, sometimes revisiting and improving them multiple times, often with successful implementations (Frei, 2003). Some have developed site selection protocols that align with general World Meteorological Organization (WMO) standards, adapting or extending them to meet the specific needs of their territories and intended applications (Rojas Briceño et al., 2021; Theochari et al., 2021).

The Dominican Republic, an island nation in the Caribbean occupying the eastern two-thirds of Hispaniola, is characterized by its diverse geography, including coastal plains, mountain ranges, and a tropical climate. This geographical diversity, combined with its socioeconomic challenges, makes the country highly vulnerable to the impacts of climate change, and an insufficient WS network exacerbates this vulnerability (Izzo et al., 2010; Lincoln Lenderking et al., 2020; Lohmann, 2016; Mackay & Spencer, 2017; Ngoc Le, 2019; Roson, 2013). Improving and expanding the WS network requires investment in technology and infrastructure, as well as partnerships among government agencies, private entities, and research institutions (Programa Mundial de Alimentos (PMA), 2019). However, to optimize the use of limited resources, it is critical to design, evaluate, and select network alternatives using weighted criteria.

Research on the design of weather station networks consistently identifies multi-criteria decision-making (MCDM) methods as ideal for this purpose (Köksalan et al., 2011; Taherdoost & Madanchian, 2023; Thiriez & Zionts, 1975). These methods leverage geospatial data and include public input spatially integrated into decision-making using Geographic Information Systems (GIS) (Chakhar & Mousseau, 2008; Eastman et al., 1998; Malczewski, 2004; Rojas Briceño et al., 2021; Tekleyohannes et al., 2021; Theochari et al., 2021). Studies have demonstrated the effectiveness of traditional geostatistical techniques (Ali & Othman, 2018; Valipour et al., 2019), contemporary deep learning algorithms in combination with traditional methods (Safavi et al., 2021), and entropy-based approaches (Bertini et al., 2021). Combining geospatial data (e.g., GIS and remote sensing) with multi-criteria analysis (MCA) that assigns relative weights to geographical criteria is particularly efficient for analyzing diverse variables (Rojas Briceño et al., 2021).

The Analytic Hierarchy Process (AHP), a well-established multi-criteria decision-making (MCDM) method, is widely used due to its simplicity, its ability to provide insights into the analyzed attributes, and its structured framework for incorporating expert input (Rojas Briceño et al., 2021). Developed by Thomas Saaty in the 1970s (Saaty, 1977) and refined in subsequent decades (Saaty, 2001; Saaty & Tran, 2007), AHP is used to make decisions involving multiple criteria and alternatives. Traditionally applied in engineering, social sciences, economics, and business, AHP has recently been utilized effectively for selecting optimal WS sites in Peru (Rojas Briceño et al., 2021). AHP involves breaking down a complex problem into a hierarchical structure of criteria and subcriteria, followed by pairwise comparisons to assign relative importance (Saaty & Tran, 2007). The process includes identifying objectives and criteria, structuring them hierarchically, conducting pairwise comparisons, calculating priority values for criteria, and ranking alternatives based on aggregated priorities.

In this study, we integrate the Analytical Hierarchy Process (AHP) with geospatial and expert-driven data to systematically identify optimal sites for meteorological and climatic stations in the Dominican Republic. We prioritize key environmental and accessibility criteria to maximize spatial and resource efficiency while minimizing redundancy in existing networks. Additionally, we propose actionable scenarios for network expansion that align with international standards, offering solutions to address data gaps in poorly covered regions. Through this research, we advance geospatial methodologies and decision-support frameworks for meteorological infrastructure planning, with potential applications in broader climatological and environmental sciences.

2 Materials and Methods

We applied a sequence of four interdependent steps to develop alternative designs for weather station (WS) networks, emphasizing the multi-criteria selection of sites prioritized for their deployment. First, we gathered data on the existing WS network through consultations (via forms and visits) with government agencies, including the Dominican National Meteorological Office (ONAMET, now the Dominican Institute of Meteorology, INDOMET) and the National Institute of Hydraulic Resources (INDRHI). These forms were created and managed using the Open Data Kit (ODK) platform (Get ODK Inc., 2024; Hartung et al., 2010). We also consulted private entities managing WS networks. These efforts resulted in consolidated information on station locations, operational status, and other relevant attributes. This step ensured that the analysis was grounded in an accurate and comprehensive understanding of the current state of the WS network.

Subsequently, we implemented an Analytic Hierarchy Process (AHP) to select the optimal option among different alternatives using selection criteria weighted by individuals with expertise in the problem (Saaty, 2013). The selected criteria were distance to access routes, thermal seasonality, rainfall seasonality, habitat heterogeneity, distance to water bodies, slope, hours of direct sunshine, elevation. These eight criteria were chosen based on their relevance to the problem, supported by our expertise as well as previous studies and recommendations from the World Meteorological Organization (Rojas Briceño et al., 2021; World Meteorological Organization (WMO) & The International Association of Hydrological Sciences, 1976).

We explicitly requested expert consultations, asking respondents to complete questionnaires electronically. After collecting the responses, we organized and recoded the data, then evaluated their consistency. Only consistent responses were used to establish the criteria weights, which were subsequently applied to the available geospatial sources. We utilized geospatial data sources available in Google Earth Engine (GEE), which were preprocessed using zonal statistics techniques and organized according to the H3 spatial index library from Uber (Gorelick et al., 2017; Martínez-Batlle, 2022; Uber Technologies, Inc., 2024). This dataset included approximately 13,000 hexagons containing multi-criteria information distributed across the Dominican Republic. For this task, we employed the GEE Python API to process the data programmatically, using packages like `geemap` for map visualization and data handling (Google Earth Engine Contributors, 2023; Wu, 2020). Finally, we assigned each hexagon an aggregated priority category, choosing from four possible options: marginally prioritized, moderately prioritized, prioritized and essential.

We designed the questionnaires, processed the responses, and weighted the criteria of geographic information sources using programming languages. These tasks were performed in the R statistical programming environment with the following packages: `ahpsurvey`, `sf`, `raster`, `terra`, `ggplot2`, `tidyverse`, `kableExtra`, `spdep`, `units`, `knitr`, and `rmarkdown` (Cho, 2019; Hijmans, 2023, 2024; Pebesma et al., 2016; Pebesma, 2018; Pebesma & Bivand, 2023; R Core Team, 2024; Wickham et al., 2019; Xie, 2014; Xie et al., 2020; Zhu, 2021). We also used Python to automate the design of questionnaires and their integration with Google Forms via its API.

Subsequently, we used the AHP results as input for a constraint-based exclusion process. In this step, we carefully analyzed the hexagons to identify those located in areas where accessibility was limited or where proximity to water bodies posed challenges. Hexagons situated near or within water bodies were deemed unsuitable for hosting meteorological stations and were excluded from further consideration. This process ensured that only feasible locations remained for the next steps of the analysis.

Finally, to optimize the spatial distribution of weather stations, we developed a custom site selection function based on neighborhood analysis. This function generated proposed station locations for three density scenarios: 100, 150, and 250 km^2 per station, aligning with the station density criteria recommended by the World Meteorological Organization (World Meteorological Organization (WMO), 2020; World Meteorological Organization (WMO) & The International Association of Hydrological Sciences, 1976). The algorithm employed convex hulls and distance maximization to iteratively select points that were maximally distant from previously chosen locations, ensuring spatial homogeneity across the coverage area. For each scenario, the coverage area was defined as the set of hexagons meeting the priority categories essential or prioritized.

To refine the proposed locations, we incorporated a neighborhood analysis that utilized continuous distance surfaces (e.g., rasters). This analysis identified and excluded proposed stations located too close to existing stations with “Good or Active” status in the INDRHI or ONAMET networks. By doing so, we avoided redundancy and ensured that the proposed distributions complemented the existing station networks while maintaining an optimal spatial configuration.

3 Results

The operational status and distribution of weather stations (WS) in 2022 reveal key differences between the networks managed by the Dominican Institute of Meteorology (INDOMET) and the National Institute of Hydraulic Resources (INDRHI). We analyzed these differences to identify coverage gaps and opportunities for improvement (Table 1). We found that INDOMET operates 87 WS, classifying 36 as “Active or Good” (41%), 51 as “Inactive or Not Reported” (59%), and none as “Recoverable.” In contrast, we observed that INDRHI’s network comprises 54 stations, with 16 classified as “Active or Good” (30%), 28 as “Inactive or Not Reported” (52%), and 10 as “Recoverable” (18%). Together, both networks include 141 stations, with 52 in “Active or Good” condition, representing 37% of the total. Considering only WS classified as “Active or Good,” the spatial representativeness of INDOMET’s network corresponds to one station per 1346 km^2, while for INDRHI’s network, it corresponds to one station per 3028 km^2.

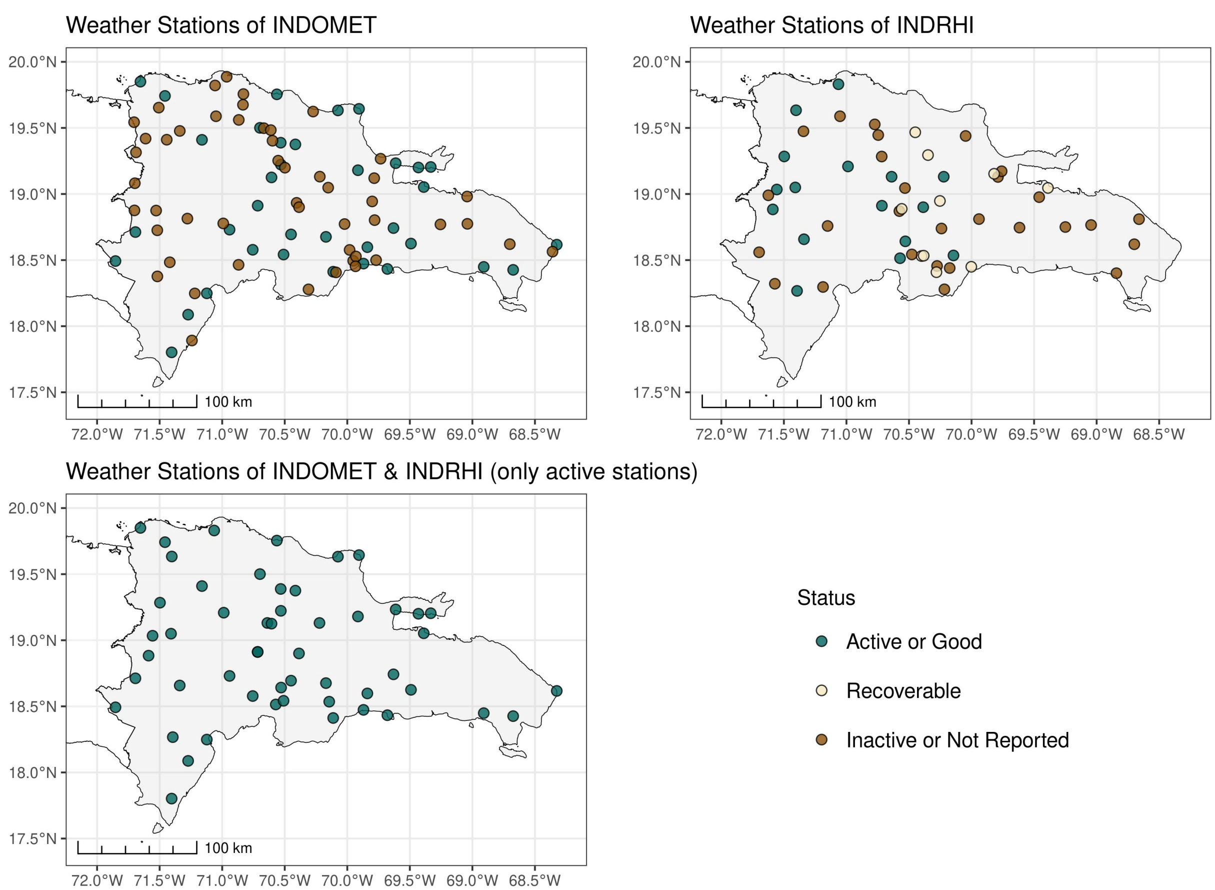

Figure 1: Weather station networks in the Dominican Republic for 2022, presented by operational status and management entities. The top two maps show stations managed by the Dominican Institute of Meteorology (INDOMET) and the National Institute of Hydraulic Resources (INDRHI), respectively, categorized as "Active or Good," "Recoverable," or "Inactive or Not Reported." The bottom map consolidates active stations from both institutions to emphasize their combined geographic coverage.

We also analyzed the geographic distribution of WS, as shown in Figure 1, and observed that INDOMET’s network provides broader coverage. We identified that a moderate proportion of INDRHI’s stations could be

Table 1: Summary of weather station status in 2022 by owner (INDOMET and INDRHI) in the Dominican Republic for 2022, including the number of active or good, inactive or not reported, and recoverable stations, along with their total counts

Owner	**Active or Good**	**Inactive or Not Reported**	**Recoverable**	**Total**
INDOMET	36	51	0	87
INDRHI	16	28	10	54
Total	52	79	10	141

Table 2: Aggregated preferences and standard deviations for the eight criteria evaluated in the Analytical Hierarchy Process (AHP) to prioritize optimal sites for weather stations in the Dominican Republic

Variable	**Aggregated Preferences**	**Standard Deviation**
rainfall seasonality	0.27	0.04
hours of direct sunshine	0.18	0.11
thermal seasonality	0.17	0.08
elevation	0.12	0.05
habitat heterogeneity	0.09	0.05
distance to access routes	0.07	0.03
distance to water bodies	0.06	0.03
slope	0.04	0.02

restored to full operational status with minimal recovery efforts. By combining the "Active or Good" WS from INDOMET and INDRHI, we also created a map that offers a comprehensive view of the functional coverage across the Dominican Republic. This map highlights critical gaps in the spatial distribution of WS and emphasizes the need to enhance monitoring in underserved areas to ensure representative weather and climate data coverage.

We used the Analytical Hierarchy Process (AHP) to provide a structured framework for prioritizing criteria and identifying optimal sites for weather stations, ensuring an objective and expert-driven selection process. From the eight preselected criteria evaluated by experts, the four with the highest aggregated weights, in descending order, are rainfall seasonality, hours of direct sunshine, thermal seasonality and elevation. We detailed the aggregated prefference of each criterion, along with its standard deviation, in Table 2.

We evaluated and prioritized candidate sites for WS in the Dominican Republic by reclassifying the spatial criteria into four ordinal priority levels: essential, prioritized, moderately prioritized and marginally prioritized. We summarized the specific intervals applied for each of the eight evaluated criteria, including distance to access routes, distance to water bodies, elevation, habitat heterogeneity, hours of direct sunshine, rainfall seasonality, slope, and thermal seasonality, in Table 3. We illustrated the spatial distribution of these reclassified criteria in Figure 2, which highlights the varying proportions of areas assigned to each priority level. Criteria such as rainfall seasonality and thermal seasonality displayed relatively balanced territorial distributions across the four priority levels. In contrast, we observed that criteria like hours of direct sunshine and elevation concentrated priority areas (essential and prioritized) in specific regions. This pattern reflects how we aligned the selected criteria with the unique environmental and geographical characteristics of the Dominican Republic, thereby informing the strategic expansion of the WS network.

We analyzed the reclassified scores for each criterion and observed wide variability in the area covered by each priority category (see Table 4). Based on the AHP results, we assigned high weights to rainfall and thermal seasonality, which balanced the territory proportions relatively evenly across the four priority classes. In contrast, we noticed that the criterion for hours of direct sunshine led to a significant concentration of areas

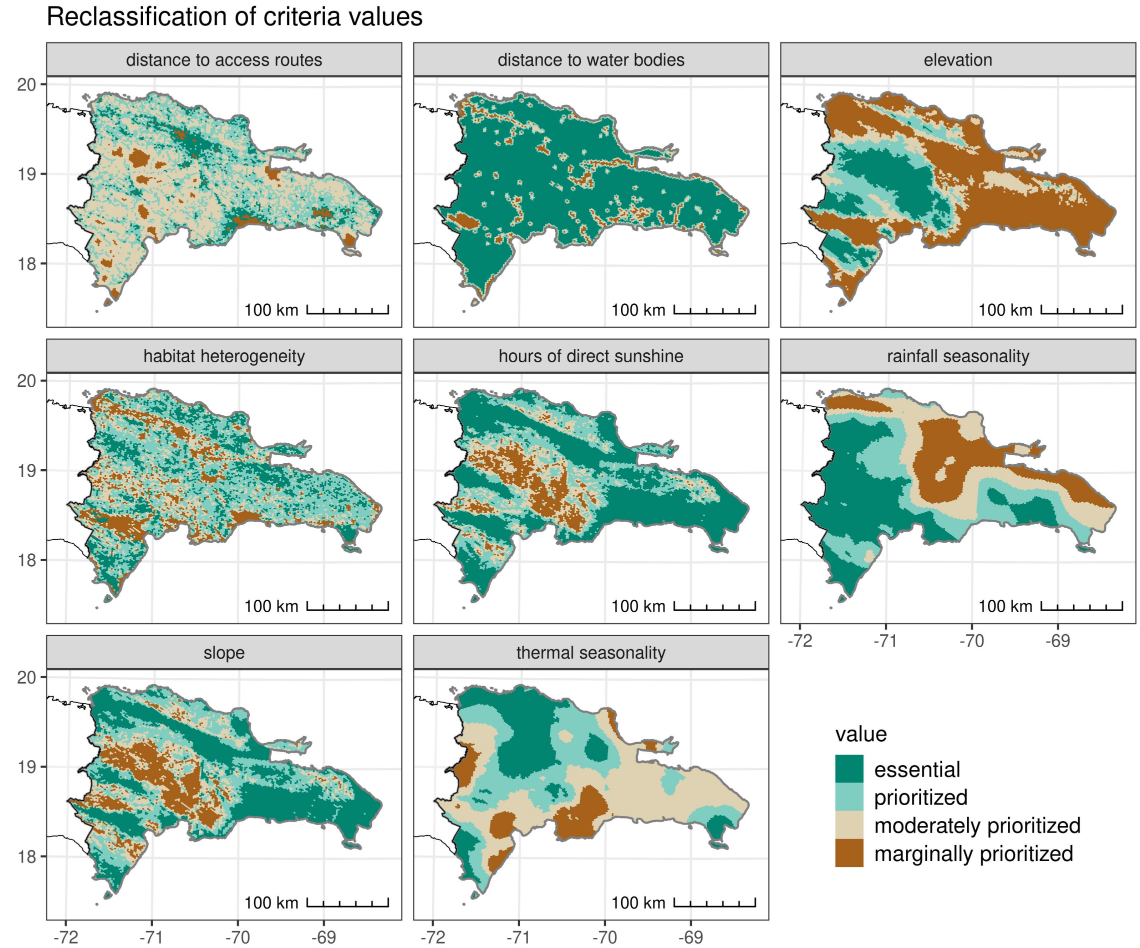

Figure 2: Reclassification of criteria values for weather station site selection across the Dominican Republic. Each panel represents the spatial distribution of priority categories (essential, prioritized, moderately prioritized, and marginally prioritized) for one of the evaluated criteria: distance to access routes, distance to water bodies, elevation, habitat heterogeneity, hours of direct sunshine, rainfall seasonality, slope, and thermal seasonality

classified as high-priority for establishing weather stations, including "prioritized" and "essential". Similarly, we identified numerous hexagons categorized as "prioritized" and "essential" under the elevation criterion. This result highlights how the Dominican Republic's mountainous regions, with the lowest WS density, drove us to prioritize elevated topography for establishing new stations.

We analyzed the distribution of aggregated categories before and after applying exclusion based on limiting factors, highlighting key differences in spatial coverage and proportional areas. Initially, the aggregated categories without exclusions showed a dominance of intermediate priorities, as moderately prioritized and prioritized accounted for 70% of the total studied area, while marginally prioritized and essential shared the remaining 30% (Table 5, second column). These categories were spatially well distributed across the Dominican Republic (Figure 3, left), reflecting the AHP method's focus on prioritizing areas with favorable environmental and geographical attributes. High-priority hexagons (prioritized and essential) were mainly located in regions with high seasonality, particularly in mountainous areas and along the eastern edge of the country, which also exhibited good performance in hours of sunshine. Conversely, hexagons categorized as marginally prioritized were predominantly found in lower elevation areas with limited sunshine hours, steep slopes, and low thermal and rainfall seasonality.

After applying exclusion based on limiting factors, the distribution of aggregated categories revealed significant changes in both spatial patterns and proportional coverage. A total of 1508 hexagons were assigned the

Table 3: Thresholds used for reclassifying the average values of eight spatial criteria into four ordinal priority levels (essential, prioritized, moderately prioritized, and marginally prioritized) for weather station site selection in the Dominican Republic. Each row corresponds to a criterion, showing the intervals defined by the research team based on expert knowledge and bibliographic references.

Variable	**Essential**	**Prioritized**	**Moderately prioritized**	**Marginally prioritized**
distance to access routes	(50,200]	(200,500]	(500,5e+03]	[12.8,50] and (5e+03,3.28e+04]
thermal seasonality	(1.5,1.87]	(1.3,1.5]	(1.1,1.3]	[0.573,1.1]
rainfall seasonality	(50,89.6]	(40,50]	(30,40]	[19.5,30]
habitat heterogeneity	[0,300]	(300,450]	(450,600]	(600,3.56e+03]
distance to water bodies	(3e+03,2.64e+04]	(2e+03,3e+03]	(1e+03,2e+03]	[0,1e+03]
slope	[0,3]	(3,9]	(9,15]	(15,32.7]
hours of direct sunshine	(4.3e+03,4.48e+03]	(4.1e+03,4.3e+03]	(3.9e+03,4.1e+03]	[3.18e+03,3.9e+03]
elevation	(800,2.79e+03]	(400,800]	(200,400]	[-42,200]

Table 4: Percentage of area by criteria used in the selection process for optimal weather station sites, emphasizing each criterion's contribution to the prioritization framework

Variable	**Essential**	**Prioritized**	**Moderately prioritized**	**Marginally prioritized**	**Total**
distance to access routes	11.54	33.77	48.85	5.84	100
thermal seasonality	22.17	28.11	38.39	11.33	100
rainfall seasonality	33.90	22.95	21.67	21.47	100
habitat heterogeneity	19.88	43.74	20.16	16.22	100
distance to water bodies	75.04	8.04	8.72	8.20	100
slope	39.60	28.86	16.92	14.63	100
hours of direct sunshine	48.23	25.06	16.03	10.68	100
elevation	17.05	16.03	16.53	50.39	100

category marginally prioritized due to their proximity to water bodies, location within populated areas, or remoteness in terms of accessibility. These excluded areas included inland and coastal lakes and lagoons, coastal zones, wide rivers, reservoirs, and inaccessible mountainous regions. As shown in Figure 3 (right), the updated distribution reflects a refinement in prioritization, ensuring that the remaining areas meet the necessary conditions for weather station placement. The proportional areas of the aggregated categories after exclusion are summarized in Table 5 (third column), highlighting a redistribution that prioritizes feasible and representative locations for weather stations.

Our final step involved proposing site locations based on the priority categories and criteria established in the earlier stages. These proposals aim to address gaps in the existing weather station network by suggesting new locations that meet the requirements of either essential or prioritized. Using the refined spatial distribution after exclusions, we generated three scenarios with varying station densities: 100, 150, and 250 km^2 per station. Each scenario represents an optimized distribution of proposed sites, tailored to achieve comprehensive spatial coverage while considering practical constraints and priorities.

In the first scenario (Figure 4, top), where each station covers 100 km^2 of area, we recommend the installation of 170 new stations. The map clearly distinguishes the proposed sites categorized as "prioritized" and "essential". The proposed "essential" sites are predominantly concentrated in the central and eastern regions of the Dominican Republic, particularly along mountainous areas and regions with higher elevation. In contrast,

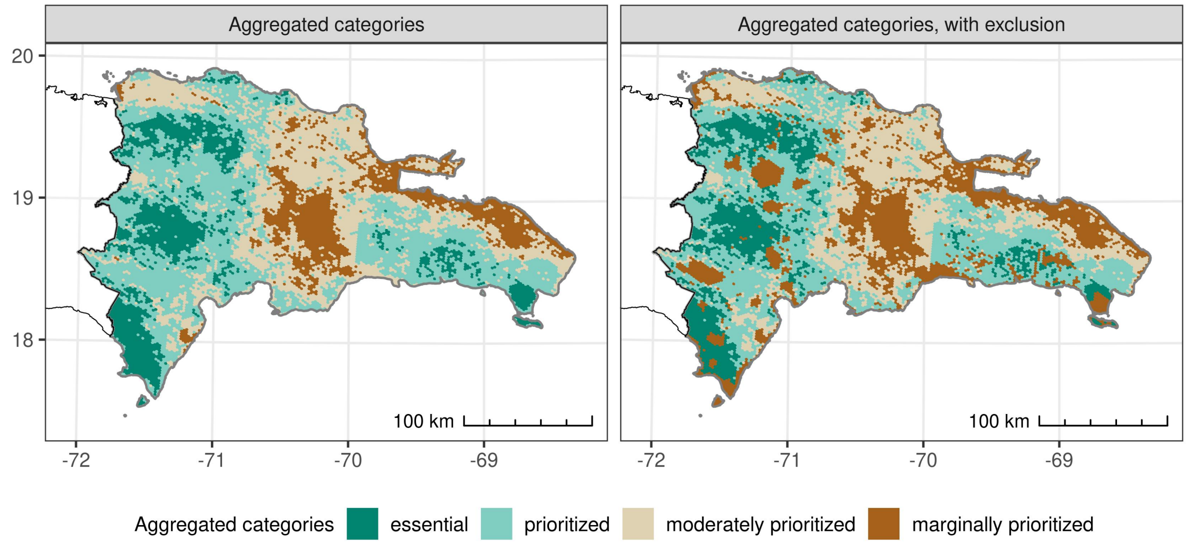

Figure 3: Map of aggregated categories, with and without exclusion based on limiting factors

Table 5: Percentage of area covered by aggregated categories for weather station site selection, with and without exclusion based on limiting factors

Aggregated category	**Without exclusion**	**With exclusion**
Marginally prioritized	13.79	24.08
Moderately prioritized	30.81	26.95
Prioritized	39.62	34.39
Essential	15.77	14.59
Total	100.00	100.00

"prioritized" sites show a broader distribution, extending into the northern and southern regions, covering a mix of coastal areas and lowlands. Notably, the southern coastal plains, lowlands, and mid-altitude regions feature a higher proportion of prioritized sites, highlighting the emphasis on coverage in areas with fewer terrain and environmental constraints. In the northeast and central DR, proposed sites are scattered, with a focus on bridging gaps in spatial coverage in flatter, lower-priority regions.

Expanding on the analysis, the second scenario (Figure 4, middle) assumed a coverage of 150 km^2 per station. We followed a similar process and recommended installing 89 new stations. The map distinguished the proposed sites categorized as "prioritized" and "essential", and showed how the spatial distribution shifted notably compared to the first scenario. Our proposal concentrated "essential" sites in the central and western regions, particularly in mountainous areas and regions with complex terrain, though their density decreased slightly due to the existing broader station coverage in the east region. In contrast, "prioritized" sites spread more evenly across the country, with a marked presence in valleys and plains. This scenario demonstrated our effort to balance the inclusion of essential and prioritized areas while maintaining a cohesive spatial configuration. Additionally, we extended coverage into areas less emphasized in the first scenario, particularly along the central valleys and northern slopes, further bridging gaps in the network.

In the third scenario, with a coverage of 250 km^2 per station, we recommended installing 39 new stations (Figure 4, bottom). The resulting map emphasizes the focus on maximizing coverage in priority areas while ensuring efficient resource allocation. Proposed sites in "essential" areas were primarily located in the central and western regions, continuing the pattern observed in previous scenarios. However, their distribution became more dispersed due to the lower station density. On the other hand, "prioritized" dominated across the country, particularly in areas where terrain and environmental constraints are less severe. This scenario

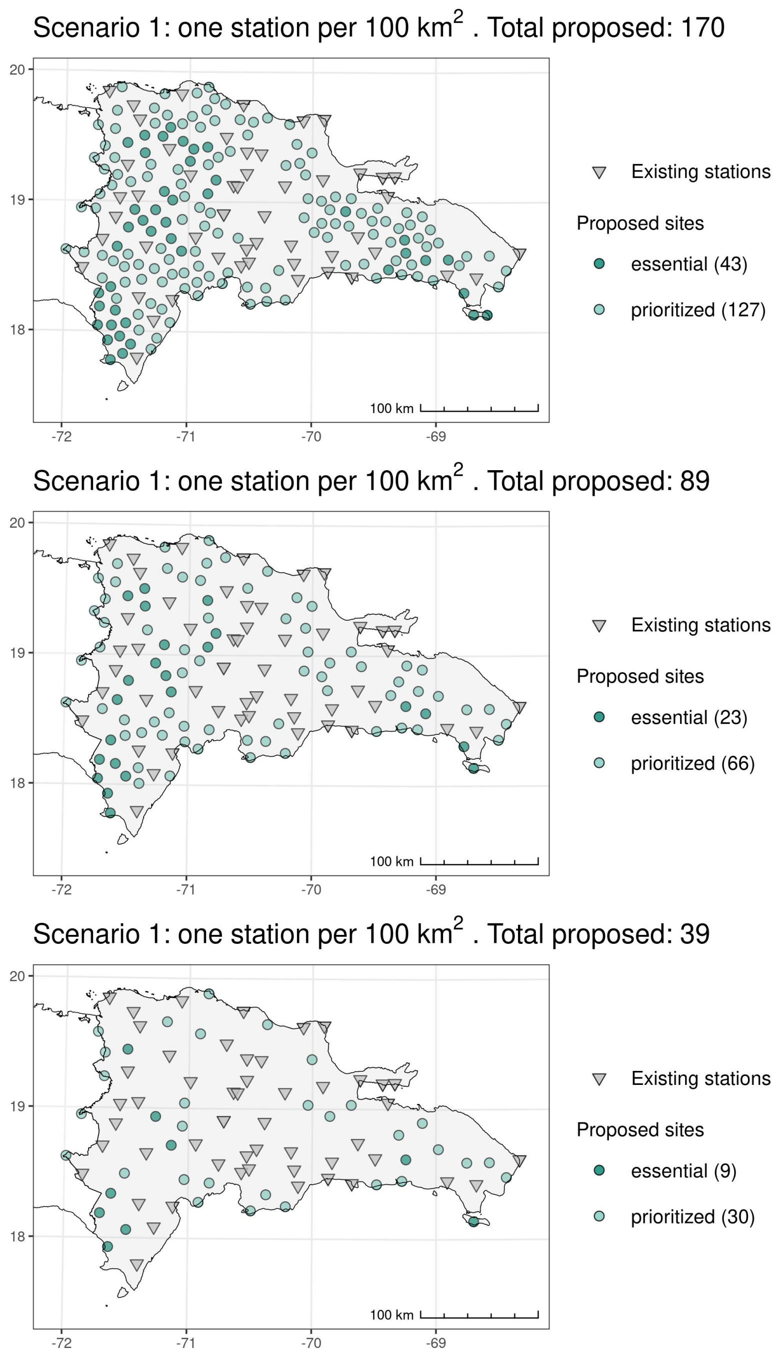

Figure 4: Spatial distribution of existing and proposed weather stations (WS) under three different scenarios of station density in the Dominican Republic: one station per 100 km^2 (top), 150 km^2 (middle), and 250 km^2 (bottom). Existing stations are represented by inverted triangles, while proposed sites are represented by circles. The proposed sites are classified into two categories: "essential" and "prioritized," with their respective counts shown in the legend. Proposed sites have been selected to avoid redundancy with existing stations in "Good or Active" condition managed by INDOMET and INDRHI

also extended coverage to underrepresented regions in the northwest, filling significant gaps in the spatial distribution. The broader spacing of stations in this scenario highlights the trade-offs involved in balancing territorial coverage, resource efficiency, and budget constraints.

4 Discussion

We successfully achieved the primary objectives of this study by integrating geospatial analysis with the Analytic Hierarchy Process (AHP) to propose optimal site locations for weather stations (WS) in the Dominican Republic. This approach allowed us to systematically address gaps in the existing network and align new site proposals with environmental, accessibility, and governance priorities (Izzo et al., 2010; Programa Mundial de Alimentos (PMA), 2019).

The results demonstrate the value of combining multi-criteria decision-making (MCDM) methods with neighborhood analysis for spatial planning. Key findings include the identification of high-priority areas based on thermal and rainfall seasonality, elevation, and solar radiation, which collectively emphasize the importance of elevated regions with significant climatic variability (Izzo et al., 2010; Rojas Briceño et al., 2021). These results align with previous studies highlighting the role of these variables in optimizing WS placement, but our study advances the field by explicitly incorporating redundancy constraints through a neighborhood-based exclusion process using a custom-developed function.

Our methodological approach offers several innovations compared to previous studies. First, the use of the H3 hexagonal indexing system enhanced the spatial resolution and computational efficiency of zonal statistics. Second, the integration of geospatial tools like Google Earth Engine (GEE) with AHP allowed us to streamline the workflow, facilitating the prioritization of thousands of candidate sites across the Dominican Republic. Third, the disaggregation of proposed sites into "essential" and "prioritize" categories introduces a flexible framework for decision-makers to allocate resources according to budget constraints and governance structures.

The scenarios generated for station densities—100, 150, and 250,km^2 per station—provide practical pathways for WS network expansion, while simultaneously adhering to the recommendations of national and international entities (Programa Mundial de Alimentos (PMA), 2019; World Meteorological Organization (WMO) & The International Association of Hydrological Sciences, 1976). Each scenario reflects trade-offs between spatial coverage and resource efficiency, offering stakeholders the flexibility to adapt the recommendations to evolving priorities. Notably, our results show that higher-density scenarios (e.g., 100,km^2) achieve comprehensive coverage in critical areas, while lower-density scenarios (e.g., 250,km^2) maintain representativeness with reduced resource investment.

Despite these strengths, several limitations should be acknowledged. While the proposed site locations are based on robust spatial analysis, the definitive selection of WS locations requires field validation to assess terrain constraints, local accessibility, and potential land-use conflicts. Additionally, the study's exclusion criteria focused primarily on proximity to water bodies and existing WS networks but did not account for other potential barriers, such as detailed accessibility constraints or issues related to land ownership. These factors underscore the need for complementary qualitative assessments during implementation.

Our approach also highlights opportunities for leveraging DIY and low-cost equipment in expanding WS networks, particularly in a global context where high-density data and microclimate information are increasingly demanded for specific studies (Chan et al., 2021; Theisen et al., 2020). These solutions are particularly relevant for deploying stations in prioritized areas, as they can reduce costs while maintaining sufficient data quality for certain applications (Kemppinen et al., 2024). Furthermore, integrating educational initiatives with WS deployment—such as collaborating with schools and community organizations—can enhance the sustainability and societal impact of these networks.

In conclusion, this study provides a replicable framework for WS network planning that combines advanced geospatial analysis with expert-driven criteria prioritization. The proposed methodology is not only relevant for the Dominican Republic but also adaptable to other regions facing similar challenges in optimizing WS networks. Future research should explore the integration of additional environmental variables, such as wind patterns or soil characteristics, and evaluate the long-term performance of deployed WS in capturing climatic variability. By addressing these avenues, stakeholders can further enhance the resilience and functionality of WS networks in the face of evolving climatic and societal demands.

Conflict of Interest Declaration

The authors declare that they have no conflict of interest related to the content of this article.

5 Author Contributions

JM and MI conceptualized and designed the study. JM was responsible for data collection. JM and MI established the methodology and conducted the research. JM developed the software, and supervision was carried out by MI. Both validated the work. JM and MI were in charge of visualization and drafted the original manuscript.

Data, Scripts, and Code Availability

The R scripts and typesetting files used to produce this paper, including styles, BibTeX entries for citations, figures, and tables, are available at https://github.com/geofis/seleccion-sitios-estaciones-meteoclimaticas-rd. Scripts for data curation, processing, and analysis are accessible at https://github.com/geofis/datos-meteoclimaticos-escenarios-cc and on Zenodo at https://doi.org/10.5281/zenodo.14571957. Additionally, the R images (serialized representations of R objects stored in .Rdata files) required to reproduce both the analyses and the paper itself are available at https://doi.org/10.5281/zenodo.14574177.

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