

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

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

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

21 1 Introduction

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

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

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

43 The Dominican Republic, an island nation in the Caribbean occupying the eastern two-thirds of Hispaniola,
 44 is characterized by its diverse geography, including coastal plains, mountain ranges, and a tropical climate.
 45 This geographical diversity, combined with its socioeconomic challenges, makes the country highly vulnerable
 46 to the impacts of climate change, and an insufficient WS network exacerbates this vulnerability (Izzo et al.,
 47 2010; Lincoln Lenderking et al., 2020; Lohmann, 2016; Mackay & Spencer, 2017; Ngoc Le, 2019; Roson, 2013).
 48 Improving and expanding the WS network requires investment in technology and infrastructure, as well as
 49 partnerships among government agencies, private entities, and research institutions (Programa Mundial de
 50 Alimentos (PMA), 2019). However, to optimize the use of limited resources, it is critical to design, evaluate,
 51 and select network alternatives using weighted criteria.

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

62 The Analytic Hierarchy Process (AHP), a well-established multi-criteria decision-making (MCDM) method, is
 63 widely used due to its simplicity, its ability to provide insights into the analyzed attributes, and its structured
 64 framework for incorporating expert input (Rojas Briceño et al., 2021). Developed by Thomas Saaty in the
 65 1970s (Saaty, 1977) and refined in subsequent decades (Saaty, 2001; Saaty & Tran, 2007), AHP is used
 66 to make decisions involving multiple criteria and alternatives. Traditionally applied in engineering, social
 67 sciences, economics, and business, AHP has recently been utilized effectively for selecting optimal WS sites
 68 in Peru (Rojas Briceño et al., 2021). AHP involves breaking down a complex problem into a hierarchical
 69 structure of criteria and subcriteria, followed by pairwise comparisons to assign relative importance (Saaty
 70 & Tran, 2007). The process includes identifying objectives and criteria, structuring them hierarchically,
 71 conducting pairwise comparisons, calculating priority values for criteria, and ranking alternatives based on
 72 aggregated priorities.

73 In this study, we integrate the Analytical Hierarchy Process (AHP) with geospatial and expert-driven data
 74 to systematically identify optimal sites for meteorological and climatic stations in the Dominican Republic.
 75 We prioritize key environmental and accessibility criteria to maximize spatial and resource efficiency while

76 minimizing redundancy in existing networks. Additionally, we propose actionable scenarios for network
77 expansion that align with international standards, offering solutions to address data gaps in poorly covered
78 regions. Through this research, we advance geospatial methodologies and decision-support frameworks for
79 meteorological infrastructure planning, with potential applications in broader climatological and environmental
80 sciences.

81 2 Materials and Methods

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

91 Subsequently, we implemented an Analytic Hierarchy Process (AHP) to select the optimal option among
92 different alternatives using selection criteria weighted by individuals with expertise in the problem (Saaty,
93 2013). The selected criteria were distance to access routes, thermal seasonality, rainfall seasonality, habitat
94 heterogeneity, distance to water bodies, slope, hours of direct sunshine, elevation. These eight criteria were
95 chosen based on their relevance to the problem, supported by our expertise as well as previous studies
96 and recommendations from the World Meteorological Organization (Rojas Briceño et al., 2021; World
97 Meteorological Organization (WMO) & The International Association of Hydrological Sciences, 1976).

98 We explicitly requested expert consultations, asking respondents to complete questionnaires electronically.
99 After collecting the responses, we organized and recoded the data, then evaluated their consistency. Only
100 consistent responses were used to establish the criteria weights, which were subsequently applied to the
101 available geospatial sources. We utilized geospatial data sources available in Google Earth Engine (GEE),
102 which were preprocessed using zonal statistics techniques and organized according to the H3 spatial index
103 library from Uber (Gorelick et al., 2017; Martínez-Batlle, 2022; Uber Technologies, Inc., 2024). This
104 dataset included approximately 13,000 hexagons containing multi-criteria information distributed across the
105 Dominican Republic. For this task, we employed the GEE Python API to process the data programmatically,
106 using packages like `geemap` for map visualization and data handling (Google Earth Engine Contributors,
107 2023; Wu, 2020). Finally, we assigned each hexagon an aggregated priority category, choosing from four
108 possible options: marginally prioritized, moderately prioritized, prioritized and essential.

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

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

121 Finally, to optimize the spatial distribution of weather stations, we developed a custom site selection function
122 based on neighborhood analysis. This function generated proposed station locations for three density
123 scenarios: 100, 150, and 250 km² per station, aligning with the station density criteria recommended by the
124 World Meteorological Organization (World Meteorological Organization (WMO), 2020; World Meteorological
125 Organization (WMO) & The International Association of Hydrological Sciences, 1976). The algorithm
126 employed convex hulls and distance maximization to iteratively select points that were maximally distant
127 from previously chosen locations, ensuring spatial homogeneity across the coverage area. For each scenario,
128 the coverage area was defined as the set of hexagons meeting the priority categories essential or prioritized.

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

134 **3 Results**

135 The operational status and distribution of weather stations (WS) in 2022 reveal key differences between the
 136 networks managed by the Dominican Institute of Meteorology (INDOMET) and the National Institute of
 137 Hydraulic Resources (INDRHI). We analyzed these differences to identify coverage gaps and opportunities
 138 for improvement (Table 1). We found that INDOMET operates 87 WS, classifying 36 as “Active or Good”
 139 (41%), 51 as “Inactive or Not Reported” (59%), and none as “Recoverable.” In contrast, we observed that
 140 INDRHI’s network comprises 54 stations, with 16 classified as “Active or Good” (30%), 28 as “Inactive or
 141 Not Reported” (52%), and 10 as “Recoverable” (18%). Together, both networks include 141 stations, with
 142 52 in “Active or Good” condition, representing 37% of the total. Considering only WS classified as “Active
 143 or Good,” the spatial representativeness of INDOMET’s network corresponds to one station per 1346 km²,
 144 while for INDRHI’s network, it corresponds to one station per 3028 km².

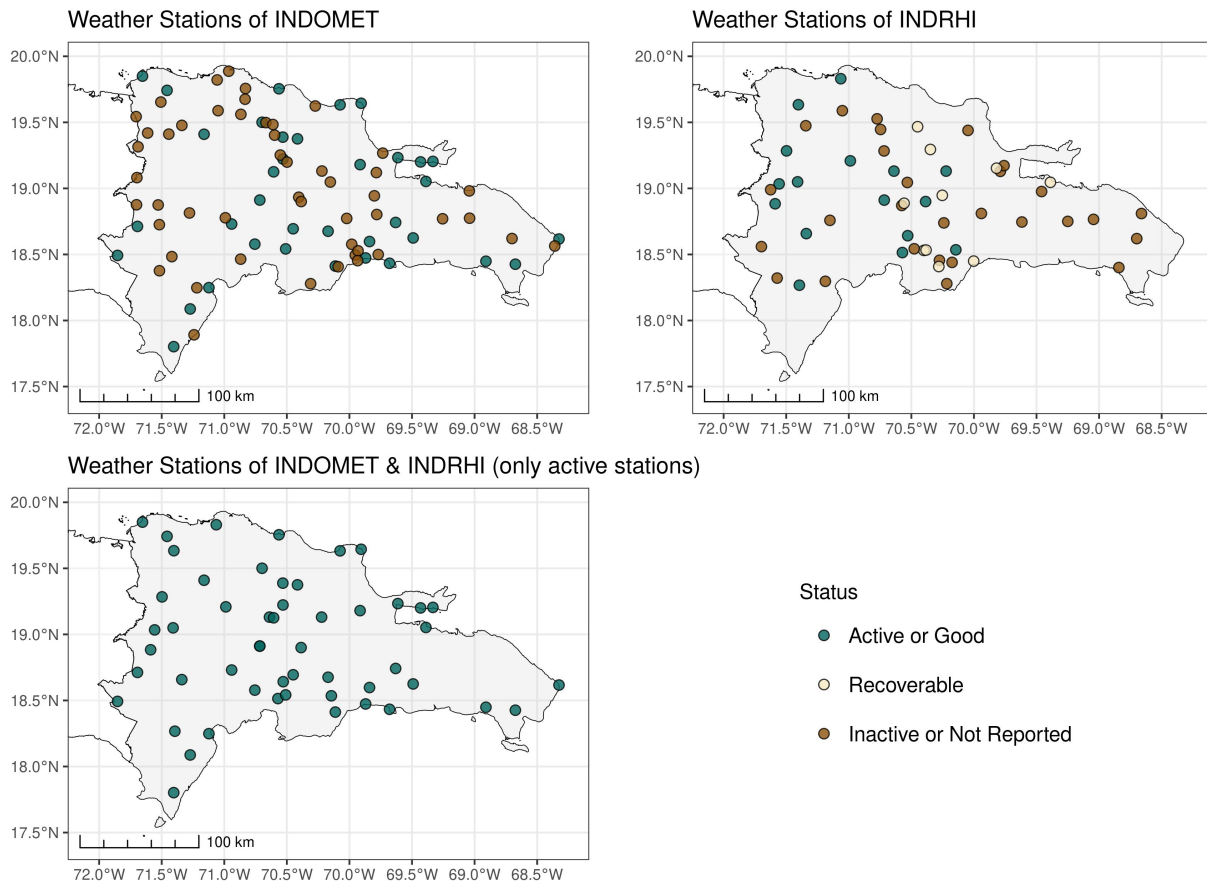


Figure 1: Weather station networks in the Dominican Republic for 2022, presented by operational status and management entities. The top two maps show stations managed by the Dominican Institute of Meteorology (INDOMET) and the National Institute of Hydraulic Resources (INDRHI), respectively, categorized 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.

145 We also analyzed the geographic distribution of WS, as shown in Figure 1, and observed that INDOMET’s
 146 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

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

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

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

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

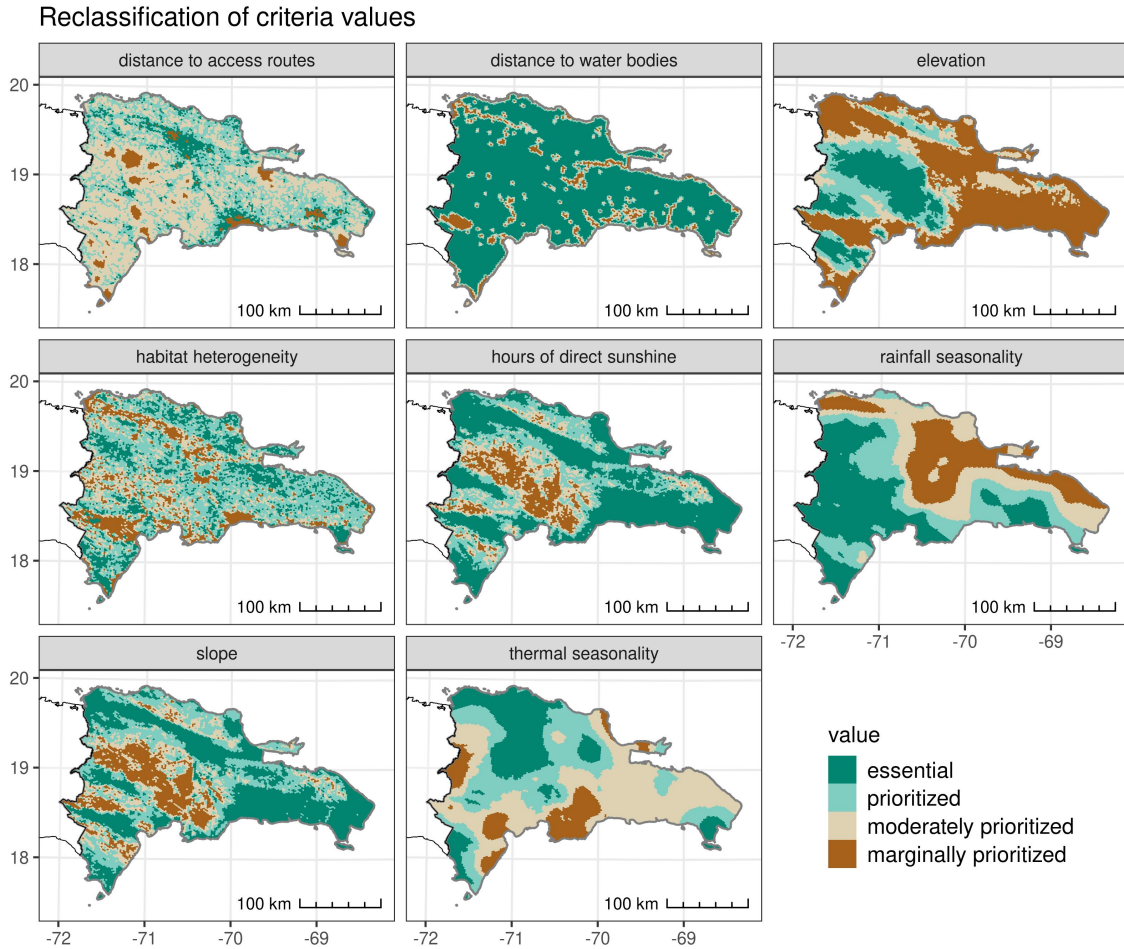


Figure 2: Reclassification of criteria values for weather station site selection across the Dominican Republic. Each panel represents the spatial distribution of priority categories (essential, prioritized, moderately prioritized, and marginally prioritized) for one of the evaluated criteria: distance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

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

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

187 After applying exclusion based on limiting factors, the distribution of aggregated categories revealed significant
 188 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

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

196 Our final step involved proposing site locations based on the priority categories and criteria established in the
 197 earlier stages. These proposals aim to address gaps in the existing weather station network by suggesting new
 198 locations that meet the requirements of either essential or prioritized. Using the refined spatial distribution
 199 after exclusions, we generated three scenarios with varying station densities: 100, 150, and 250 km² per station.
 200 Each scenario represents an optimized distribution of proposed sites, tailored to achieve comprehensive spatial
 201 coverage while considering practical constraints and priorities.

202 In the first scenario (Figure 4, top), where each station covers 100 km² of area, we recommend the installation
 203 of 170 new stations. The map clearly distinguishes the proposed sites categorized as “prioritized” and
 204 “essential”. The proposed “essential” sites are predominantly concentrated in the central and eastern regions of
 205 the Dominican Republic, particularly along mountainous areas and regions with higher elevation. In contrast,

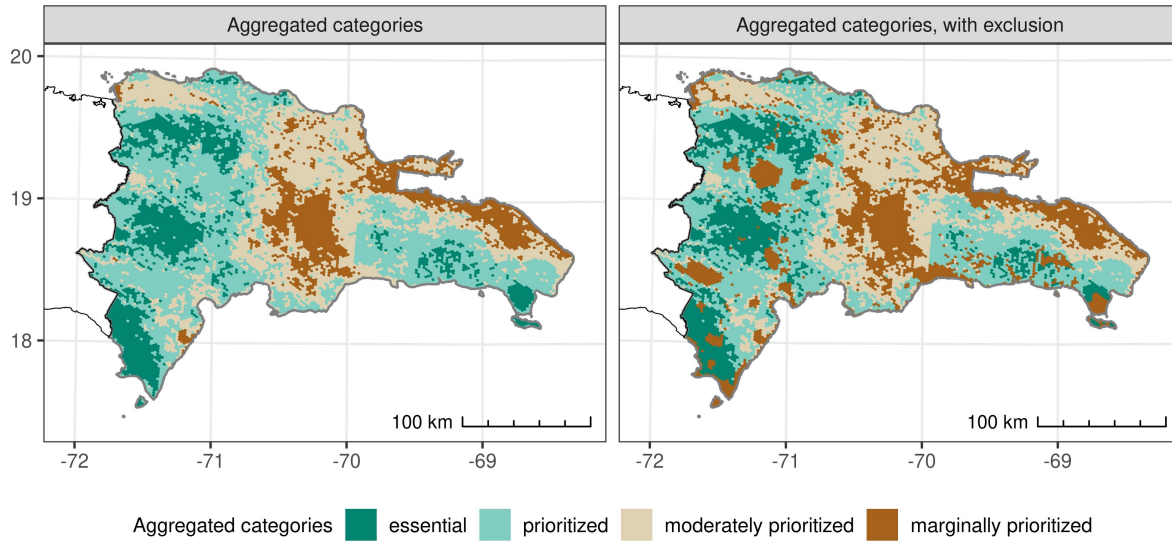


Figure 3: Map of aggregated categories, with and without exclusion based on limiting factors

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

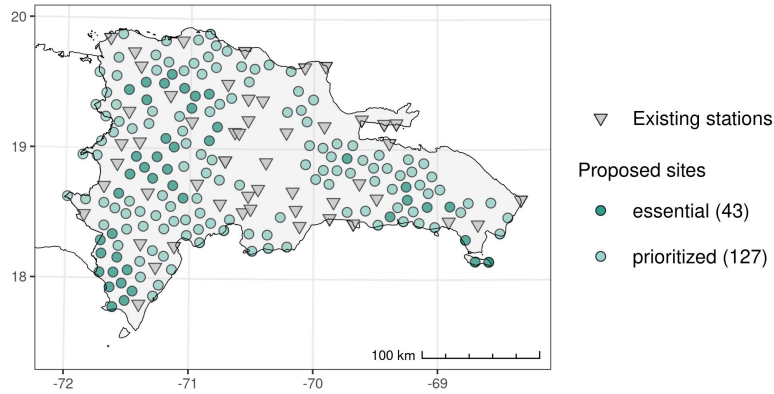
Aggregated category	Without exclusion	With exclusion
Marginally prioritized	13.79	24.08
Moderately prioritized	30.81	26.95
Prioritized	39.62	34.39
Essential	15.77	14.59
Total	100.00	100.00

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

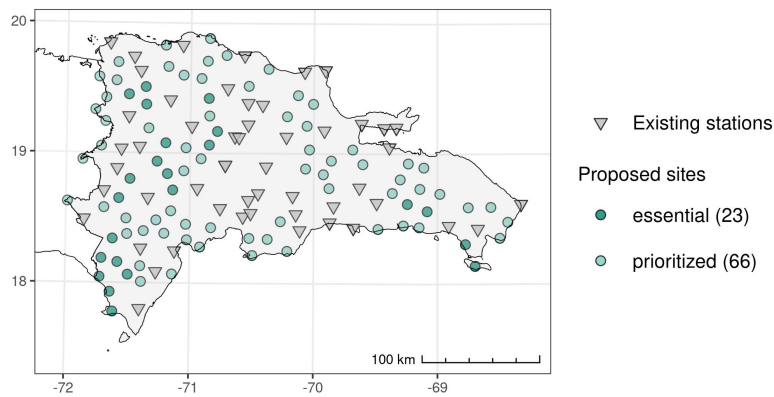
211 Expanding on the analysis, the second scenario (Figure 4, middle) assumed a coverage of 150 km² per station.
 212 We followed a similar process and recommended installing 89 new stations. The map distinguished the
 213 proposed sites categorized as “prioritized” and “essential”, and showed how the spatial distribution shifted
 214 notably compared to the first scenario. Our proposal concentrated “essential” sites in the central and western
 215 regions, particularly in mountainous areas and regions with complex terrain, though their density decreased
 216 slightly due to the existing broader station coverage in the east region. In contrast, “prioritized” sites spread
 217 more evenly across the country, with a marked presence in valleys and plains. This scenario demonstrated
 218 our effort to balance the inclusion of essential and prioritized areas while maintaining a cohesive spatial
 219 configuration. Additionally, we extended coverage into areas less emphasized in the first scenario, particularly
 220 along the central valleys and northern slopes, further bridging gaps in the network.

221 In the third scenario, with a coverage of 250 km² per station, we recommended installing 39 new stations
 222 (Figure 4, bottom). The resulting map emphasizes the focus on maximizing coverage in priority areas while
 223 ensuring efficient resource allocation. Proposed sites in “essential” areas were primarily located in the central
 224 and western regions, continuing the pattern observed in previous scenarios. However, their distribution
 225 became more dispersed due to the lower station density. On the other hand, “prioritized” dominated across
 226 the country, particularly in areas where terrain and environmental constraints are less severe. This scenario

Scenario 1: one station per 100 km² . Total proposed: 170



Scenario 2: one station per 150 km² . Total proposed: 89



Scenario 3: one station per 250 km² . Total proposed: 39

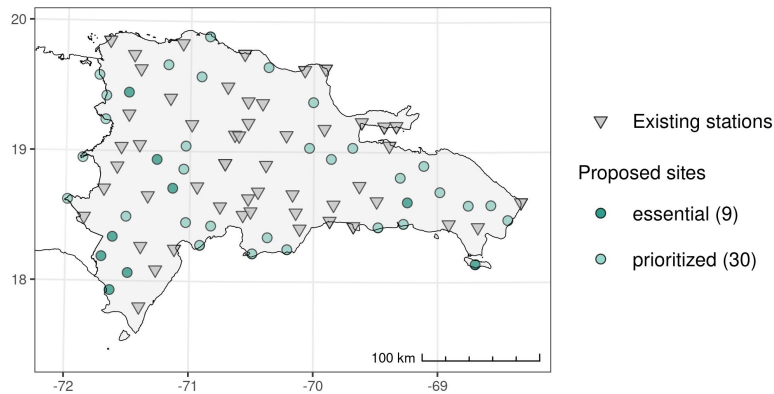


Figure 4: Spatial distribution of existing and proposed weather stations (WS) under three different scenarios of station density in the Dominican Republic: one station per 100 km² (top), 150 km² (middle), and 250 km² (bottom). Existing stations are represented by inverted triangles, while proposed sites 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

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

230 4 Discussion

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

236 The results demonstrate the value of combining multi-criteria decision-making (MCDM) methods with
 237 neighborhood analysis for spatial planning. Key findings include the identification of high-priority areas
 238 based on thermal and rainfall seasonality, elevation, and solar radiation, which collectively emphasize the
 239 importance of elevated regions with significant climatic variability (Izzo et al., 2010; Rojas Briceño et al.,
 240 2021). These results align with previous studies highlighting the role of these variables in optimizing WS
 241 placement, but our study advances the field by explicitly incorporating redundancy constraints through a
 242 neighborhood-based exclusion process using a custom-developed function.

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

250 The scenarios generated for station densities—100, 150, and 250,km² per station—provide practical pathways
 251 for WS network expansion, while simultaneously adhering to the recommendations of national and international
 252 entities (Programa Mundial de Alimentos (PMA), 2019; World Meteorological Organization (WMO) & The
 253 International Association of Hydrological Sciences, 1976). Each scenario reflects trade-offs between spatial
 254 coverage and resource efficiency, offering stakeholders the flexibility to adapt the recommendations to evolving
 255 priorities. Notably, our results show that higher-density scenarios (e.g., 100,km²) achieve comprehensive
 256 coverage in critical areas, while lower-density scenarios (e.g., 250,km²) maintain representativeness with
 257 reduced resource investment.

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

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

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

278 Conflict of Interest Declaration

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

280 **5 Author Contributions**

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

285 **Data, Scripts, and Code Availability**

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