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Optimizing Rainfall Gauge Network Density and Spacing on Ambon Island Using Thiessen Polygons and the Kagan–Rodda Approach

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Abstract

Background: Ambon Island is a small mountainous island characterized by high spatial variability of rainfall, which necessitates a representative rainfall gauge network.
Aims: This study aims to evaluate the density and spatial distribution of the rainfall station network on Ambon Island based on the standards of the World Meteorological Organization (WMO) and the Kagan–Rodda method.
Methods: This study uses annual rainfall data from 2014–2023 from eight stations, along with spatial data of the study area. Thiessen polygons were used to define the coverage area of each station in the rainfall station network. The network density was evaluated using WMO standards, and the relationship between distance and rainfall correlation was analyzed using the Kagan–Rodda method to estimate network error.
Result: The results indicate that most stations in the rainfall station network meet WMO density standards, but their spatial distribution is still uneven. The Kagan–Rodda analysis shows that more stations are needed when a smaller error is required. At a 5% error level, three stations are enough with a spacing of about 17.12 km. At a 1% error level, about 51 stations are needed with a spacing of around 4.03 km.
Conclusion: This study highlights the importance of balancing rainfall estimation accuracy with technical and practical limitations in the planning of rainfall gauge networks.

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INTRODUCTION

Hydrology plays an important role in understanding the water cycle and supporting infrastructure planning, hydrometeorological disaster mitigation, and water resource management (Baran-Gurgul & Rutkowska, 2024; Lettenmaier, 2024; Maulidiah & Darmawan, 2024). One of the main components of hydrological studies is rainfall, as it serves as an input that influences surface runoff, river flow, and water availability (Ilva et al., 2025; Muliawati et al., 2024). Reliable rainfall information is therefore essential for supporting hydrological analysis and various activities related to water resource management and disaster mitigation (Aniley et al., 2023; Hayatining Pamungkas et al., 2025).

Rainfall exhibits high spatial and temporal variability, particularly in regions with diverse geographical and topographical conditions (Chen et al., 2021; So et al., 2024). Measurements at a single location may not adequately represent rainfall conditions in the surrounding area (Li & Shao, 2025). Therefore, a rain gauge network with sufficient density and spatial distribution is required (Mnyandu & Nzimande, 2025). The representativeness of a rain gauge network is influenced by the density and spatial distribution of observation stations (Michelon et al., 2021). Low network density or uneven spatial distribution may result in inadequate representation of certain areas and increase uncertainty in areal rainfall estimation (Arrazi et al., 2024). These conditions highlight the importance of evaluating rain gauge networks to assess the adequacy of observation networks within a given area (Speight et al., 2021).

The Kagan–Rodda method has been applied in various studies to evaluate the density and requirements of rainfall station networks (Nyengere et al., 2026). Evaluated a rainfall observation network using the Kagan–Rodda method and obtained 11 recommended rainfall stations based on the network analysis (Hein et al., 2022; Jannah et al., 2023). Evaluated the density and spatial distribution of rainfall stations in Medan City using Thiessen Polygons and the Kagan–Rodda method, with the analysis indicating that the network configuration could represent the study area with an averaging error of less than 5% (Hasibuan et al., 2023; Rahmadani & Hutauruk, 2022). Applied the Kagan–Rodda method to plan rainfall station locations in the Lekso Watershed and used Thiessen Polygons to consider the area of influence of the stations, resulting in 11 planned rainfall station locations (Afifa et al., 2024). Used the Kagan–Rodda method to analyze the distribution of rainfall stations in the Bila Watershed and examined its influence on the design flood discharge (Mirsadeghi et al., 2025). Evaluated the rainfall station network in Bengkulu Province using WMO standards and the Kagan–Rodda method. Based on the WMO evaluation, 52 stations were classified as having minimum density, 22 stations as maximum density, and 42 stations as normal density (Hwang et al., 2020; Maulidiah & Darmawan, 2024). Meanwhile, the Kagan–Rodda method was analyzed at *smoothing error* levels of 1%, 2%, 3%, 4%, and 5%, with the results indicating that additional rainfall stations were still required at the selected *smoothing error* level (Hatvani et al., 2020). Furthermore, conducted a rationalization of the rainfall station network distribution in the Upper Citanduy Sub-Watershed using the Kagan–Rodda method and WMO standards to determine an appropriate number and spatial distribution of stations (Tabatabaei et al., 2022; Theochari et al., 2021). These studies were conducted in areas with different geographical extents and network conditions, ranging from watersheds to administrative regions (Eslamian et al., 2023). The network evaluation results also varied according to the conditions of each study area (Konrad & Anderson, 2023).

Ambon Island, which is part of the Maluku Islands and is classified as a small island, has hilly and mountainous topography as well as spatial variations in rainfall distribution (Rakuasa et al., 2022; Silaya & Latupapua, 2024). Based on the reviewed studies, an evaluation of the rain gauge network on Ambon Island using the Kagan–Rodda method and WMO standards has not yet been identified (Haromain et al., 2022; Megantara et al., 2022). This condition indicates the need for information on the existing rain gauge network, particularly in terms of station density and the required number of stations (Azhari et al., 2022). This study focuses on the rain gauge network on Ambon Island using the Kagan–Rodda method and WMO standards (Abdaa et al., 2021; Sunusi & Giarno, 2022). The analysis is conducted to obtain information on the density, number, and spatial distribution of the existing network, as well as its development requirements (Laude et al., 2023). Specifically, this evaluation determines whether the current infrastructure complies with international observational standards while assessing potential improvements in measurement accuracy through optimal station placement (Dikatanaya et al., 2025). The results are expected to provide supporting information for the development of the rainfall observation network and the provision of data for hydrological analysis and water resource management on Ambon Island.

METHOD

Ambon Island is geographically located at coordinates 3.57°–3.78° South Latitude and 128.10°–128.30° East Longitude, with an area of approximately 767.87 km^2, and is administratively part of Ambon City and partially Central Maluku Regency. As a small island in the Maluku Archipelago, Ambon Island is dominated by hills and mountains, with low elevations along the coast, moderate elevations in the central area, and the highest peaks located in the western and northern parts of the island.

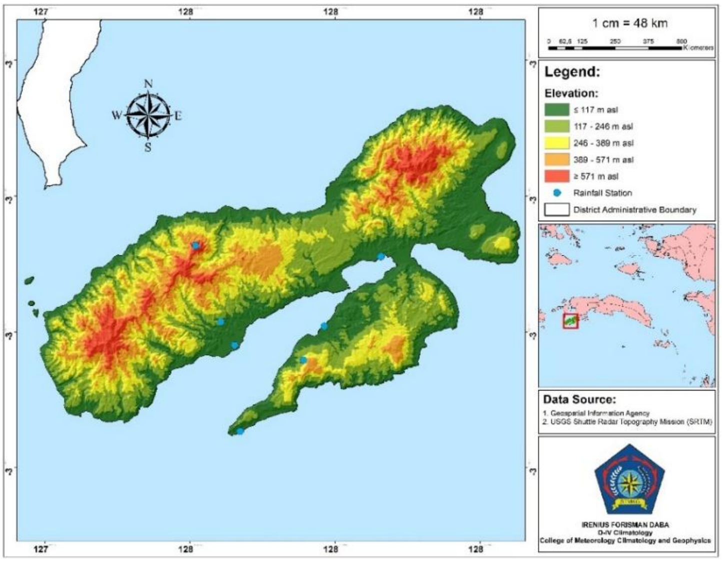

Figure 1. Map of Ambon Island

This study uses spatial data, rainfall station location data, rainfall data, and reference data for rainfall station network density. The spatial data consist of the boundary of Ambon Island in *shapefile* format, obtained from the Geospatial Information Agency (BIG), and are used as the basis for mapping and spatial analysis of the study area. Rainfall station location data, including the coordinates and number of rainfall stations on Ambon Island, were obtained from the *BMKGSoft* website to describe the existing rainfall station network.

The rainfall data cover the period from 2014 to 2023, representing a 10-year time series, and were obtained from the *BMKGSoft* website. These data serve as the primary dataset for analyzing rainfall characteristics and relationships among rainfall stations using the Kagan–Rodda method. *Climate Hazards Group InfraRed Precipitation with Station data* (CHIRPS) were used as supplementary data for periods when BMKGSoft data were unavailable. Reference data for rainfall station network density were based on the provisions and recommendations of the *World Meteorological Organization* (WMO). These references were used to evaluate the density of the rainfall station network based on the characteristics of the Ambon Island study area (Maulidiah & Darmawan, 2024), as presented in Table 1.

Table 1. Minimum Rain Gauge Density Based on WMO Guidelines

Region / Type	**Area (km^2/station)**	
	Normal Conditions	**Difficult Conditions**
Flat areas (tropical, Mediterranean, temperate)	600 – 900	3.000 – 9.000
Mountainous areas (tropical, Mediterranean, temperate)	100 – 250	1.000 – 5.000
Small mountainous islands (< 20,000 km^2) with variable rainfall	25 – 300	–
Arid and polar regions	1.500 – 10.000	–

Data Collection

The first stage involved collecting the data required for the rainfall station network analysis on Ambon Island. The collected data included the *shapefile* of the Ambon Island boundary, the coordinates of existing rainfall stations, and rainfall data for the 2014–2023 period. The *shapefile* was used to determine the boundaries and area of the study region, while the rainfall station coordinates were used to map the distribution of the existing network and as the basis for calculating inter-station distances. Rainfall data were used for data quality control and for analyzing rainfall relationships among stations using the Kagan–Rodda method.

Mapping and Spatial Analysis of Rainfall Stations

The collected rainfall station coordinates were mapped within the boundary of Ambon Island using ArcMap 10.8. Thiessen polygons were then generated based on the locations of the rainfall stations to determine the area of influence of each station. The Thiessen polygon method assumes that every point within a polygon is closer to the rainfall station located within that polygon than to any other rainfall station (Pratama & Darmawan, 2025; Rozzaq Hamidi et al., 2025). The area of each Thiessen polygon was used to calculate the areal average rainfall using the following equation:

$$\bar{P} = \frac{\sum_{i=1}^{n} A_i \, P_i}{\sum_{i=1}^{n} A_i}$$

where $\bar{P}$ where is the average areal rainfall (mm), P_i is the rainfall at the i-th rain gauge station (mm), A_i is the area of the Thiessen polygon of the i-th station (km^2), and n is the number of rain gauge stations.

Evaluation of Network Density Based on WMO Standards

The density of the existing rainfall station network was evaluated based on the criteria of the *World Meteorological Organization* (WMO) according to the physiographic characteristics of the study area. The evaluation was conducted based on the area of influence of each station to determine the network density category, namely < minimum density, normal density, and > maximum density. The percentage of the area of influence of each station relative to the total study area was calculated using the following equation:

$$P_i = \frac{A_i}{A} \times 100\%$$

where P_i = percentage of the area of influence of rainfall station i (%), A_i = area of influence of rainfall station i (km^2), and A = total area of the study region (km^2). The results were used to describe the density condition and spatial contribution of each rainfall station within the study area.

Determination of Rain Gauge Station Pairs

The Kagan–Rodda analysis was conducted using all available pairs of rain gauge stations. The number of station pairs was determined based on the number of existing rain gauge stations using the following equation:

$$N_p = \frac{n(n-1)}{2}$$

where N_p represents the number of rain gauge station pairs, while n represents the number of rain gauge stations. Each station pair was used to obtain the inter-station distance and rainfall correlation coefficient. The distance between stations was calculated based on the geographic coordinates of each station.

Analysis of Rainfall Correlation and Inter-Station Distance

The Pearson correlation coefficient was calculated for each station pair based on rainfall data for the 2014–2023 period. The correlation values were then related to the distance between stations to determine the relationship between geographic distance and similarity in rainfall patterns. This relationship was used to identify the tendency for rainfall correlation to decrease as the distance between stations increases.

Modeling the Relationship between Distance and Correlation

The relationship between inter-station distance and the correlation coefficient was modeled using an exponential function (Hidayah et al., 2022).

$$r(d) = r(0)e^{-d/d(0)}$$

where $r(d)$ represents the correlation coefficient at distance d, r_0 represents the correlation coefficient at zero distance, d represents the distance between rain gauge stations (km), and d_0 represents the correlation radius (km). The parameters r_0 and d_0 were obtained from the modeled relationship between inter-station distance and the correlation coefficient. The value of r_0 represents the theoretical correlation at zero distance, whereas d_0 represents the correlation radius describing the decrease in correlation with increasing distance.

Regression Analysis and Coefficient of Determination

The goodness of fit of the relationship between inter-station distance and the correlation coefficient was subsequently evaluated using regression analysis. The coefficient of determination (R^2) was used to determine the extent to which the relationship between inter-station distance and rainfall correlation could be explained by the model. The R^2 value was used as a measure of the goodness of fit of the relationship obtained from the paired distance and correlation data. This analysis formed part of the evaluation of the spatial relationship of rainfall in the Kagan–Rodda method.

Calculation of the Coefficient of Variation

Rainfall variability was calculated using the coefficient of variation (C_v) based on the following equation (Morales-Acuña et al., 2021):

$$C_v = \frac{\sigma}{\mu}$$

where C_v represents the coefficient of variation, σ represents the standard deviation of rainfall, and μ represents the mean rainfall. The C_v value was subsequently used as one of the parameters in calculating the Kagan–Rodda network error.

Calculation of Kagan–Rodda Network Error

The values of C_v, r_0, d_0, study area (A), and number of rain gauge stations (N) were used to calculate the averaging error (Z_1) and interpolation error (Z_3) based on the Kagan–Rodda formulation (Imaaduddiin et al., 2022; Maulidiah & Darmawan, 2024).

The averaging error was calculated as:

$$Z_1 = C_v \sqrt{\frac{1 - r_0}{N} + \frac{0.23 \cdot \sqrt{A}}{d_0 \cdot N^{1.5}}}$$

whereas the interpolation error was calculated as:

$$Z_3 = C_v \sqrt{\frac{1 - r_0}{3} + \frac{0.52 \cdot \sqrt{A}}{d_0 \cdot \sqrt{N}}}$$

The values of Z_1 and Z_3 were used to determine the required number of rain gauge stations based on the specified error level.

Sensitivity Analysis

Sensitivity analysis was conducted by calculating the required network size at several error levels. Each error level resulted in a different number of required rain gauge stations. The results were compared to determine changes in the required number of stations in response to changes in the specified error level. This analysis was used to assess the sensitivity of the recommended network to the error level applied in the Kagan–Rodda method.

Determination of the Ideal Number and Spacing of Rain Gauge Stations

The recommended number of rain gauge stations was determined based on the Kagan–Rodda calculations at the selected error level. Once the required number of stations was obtained, the ideal spacing between stations was calculated using the following equation:

$$L = 1.07 \sqrt{\frac{A}{n}}$$

where L represents the ideal spacing between rain gauge stations (km), A represents the area of the study region (km^2), and n represents the required number of rain gauge stations. The resulting ideal spacing was used as the basis for developing the recommended spatial arrangement of rain gauge stations.

Construction of the Kagan Triangle

The Kagan triangle was constructed based on the ideal inter-station distance obtained from the Kagan–Rodda analysis. The construction was performed spatially using ArcMap 10.8 by considering the locations of existing rain gauge stations and the boundaries of Ambon Island. The analysis results were used to illustrate the spatial distribution of existing rain gauge stations and potential locations for additional rain gauge stations. The resulting map was used as the basis for providing spatial recommendations for the development of the rain gauge network.

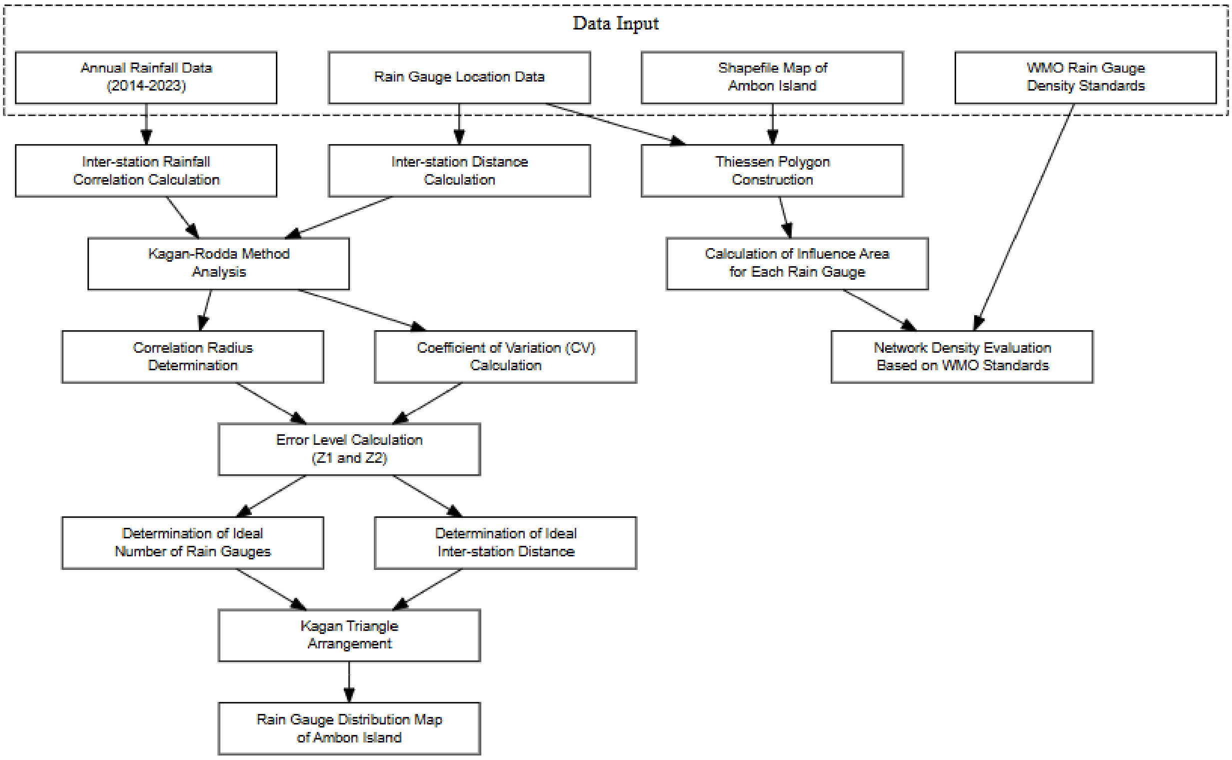

Figure 2. Flowchart

RESULTS AND DISCUSSION

Results:

Average Areal Rainfall

The Thiessen Polygon method was used to determine the area of influence of each rainfall station and to estimate the average areal rainfall over Ambon Island. The results show that the area of influence varies considerably among the eight rainfall stations, indicating an uneven spatial distribution of the existing observation network.

Passo has the largest area of influence, covering 293.95 km^2, while Oma Haruku has the smallest area of influence, covering 12.98 km^2. The average rainfall also varies among the stations. Passo records the highest average rainfall of 1,411.69 mm, whereas the Ambon Maritime Meteorological Station records the lowest average rainfall of 103.25 mm. The complete results of the Thiessen Polygon analysis are presented in Table 2.

Table 2. Results of Areal Average Rainfall Analysis

Rain Gauge Station	Area (km^2)	Average (mm)
Stasiun Meteorologi Maritim Ambon	24,64	103,25
Stamet Pattimura	156,77	723,34
Stageof Karang Panjang	82,77	386,9

Hila	147,72	484,06
Stamar Ambon	33,62	166,98
Oma Haruku	12,98	64,77
Stasiun Meteorologi Pattimura	15,42	72,36
Passo	293,95	1411,69

Evaluation of Rain Gauge Network Density Based on WMO Standards

The existing rainfall station network was evaluated using the WMO density criteria for small mountainous islands with variable rainfall. The analysis shows that five of the eight rainfall stations are classified within the normal density range, namely Stamet Pattimura, Stageof Karang Panjang, Hila, Stamar Ambon, and Passo.

Three stations, namely the Ambon Maritime Meteorological Station, Oma Haruku, and Stasiun Meteorologi Pattimura, have areas of influence below the minimum density criterion. Passo has the largest area of influence, representing 38.28% of the total study area, while Oma Haruku has the smallest area of influence, representing 1.69%. The detailed results of the WMO density evaluation are presented in Table 3.

Table 3. Results of Analysis Based on WMO Standards

Rain Gauge Station	Area (km²)	WMO Standard	Percentage (%)
Stasiun Meteorologi Maritim Ambon	24,64	< Minimum Density	3,21
Stamet Pattimura	156,77	Normal	20,42
Stageof Karang Panjang	82,77	Normal	10,78
Hila	147,72	Normal	19,24
Stamar Ambon	33,62	Normal	4,38
Oma Haruku	12,98	< Minimum Density	1,69
Stasiun Meteorologi Pattimura	15,42	< Minimum Density	2,01
Passo	293,95	Normal	38,28

Rainfall Correlation and Inter-Station Distance

The Kagan–Rodda analysis was conducted by evaluating the relationship between inter-station distance and rainfall correlation for every pair of rain gauge stations. For 8 rain gauge stations, the number of unique pairs analyzed was calculated using the following equation:

$$N_p = \frac{N(N-1)}{2}$$

resulting in:

$$N_p = \frac{8(8-1)}{2} = 28$$

Thus, a total of 28 rain gauge station pairs were obtained for the analysis. The calculated inter-station distances show variations in the spatial separation between stations, ranging from relatively close to more distant locations. The resulting inter-station distance matrix is presented in Table 4.

Table 4. Inter-Station Distance Matrix (km)

From \ To	SMMA	SMP	OH	H	SA	SKP	P	SP
SMMA	0	8,76	48,26	19,38	9,67	13,68	22,81	11,27
SMP	8,76	0	44,61	10,85	7,17	9,34	17,41	2,73
OH	48,26	44,61	0	45,56	39	35,5	27,45	45,02
H	19,38	10,85	45,56	0	15,98	15,44	18,91	8,15
SA	9,67	7,17	39	15,98	0	4,05	13,16	9,24
SKP	13,68	9,34	35,5	15,44	4,05	0	9,13	10,52
P	22,81	17,41	27,45	18,91	13,16	9,13	0	17,59
SP	11,27	2,73	45,02	8,15	9,24	10,52	17,59	0

Note: SMMA = Ambon Maritime Meteorological Station; SMP = Pattimura Meteorological Station; OH = Oma Haruku; H = Hila; SA = Stamar Ambon; SKP = Stageof Karang Panjang; P = Passo; SP = Stamet Pattimura.

Correlation analysis was performed to determine the degree of similarity in rainfall patterns between rain gauge stations. The rainfall correlation matrix between stations is presented in Table 5.

Table 5. Rainfall Correlation Matrix

	SMMA	SMP	OH	H	SA	SKP	P	SP
SMMA	1,00	0,97	0,90	0,88	0,95	0,93	0,97	0,94
SMP	0,97	1,00	0,90	0,81	0,90	0,93	0,97	0,98
OH	0,90	0,90	1,00	0,74	0,84	0,95	0,90	0,88
H	0,88	0,81	0,74	1,00	0,96	0,86	0,90	0,81
SA	0,95	0,90	0,84	0,96	1,00	0,93	0,95	0,89
SKP	0,93	0,93	0,95	0,86	0,93	1,00	0,94	0,93
P	0,97	0,97	0,90	0,90	0,95	0,94	1,00	0,97
SP	0,94	0,98	0,88	0,81	0,89	0,93	0,97	1,00

Note: SMMA = Ambon Maritime Meteorological Station; SMP = Pattimura Meteorological Station; OH = Oma Haruku; H = Hila; SA = Stamar Ambon; SKP = Stageof Karang Panjang; P = Passo; SP = Stamet Pattimura.

Rain Gauge Network Analysis Using the Kagan–Rodda Method

The rain gauge network analysis using the Kagan–Rodda method was conducted by calculating the average rainfall correlation and inter-station distance for each pair of rain gauge stations. Based on the analysis results, the average rainfall correlation ranged from 0.871–0.951, with the average inter-station distance ranging from 12.208–35.675 km **Table 6**. The relationship between rainfall correlation and inter-station distance was subsequently modeled using an exponential curve to obtain the correlation and correlation radius parameters, which were used to calculate the required rain gauge network Figure 3.

Table 6. Results of Average Rainfall Correlation and Inter-Station Distance

Rain Gauge Station	Rainfall Correlation	Inter-Station Distance
Stasiun Meteorologi Maritim Ambon	0,943	16,729
Stasiun Meteorologi Pattimura	0,932	12,609
Oma Haruku	0,888	35,675
Hila	0,871	16,784
Stamar Ambon	0,927	12,284
Stageof Karang Panjang	0,935	12,208
Passo	0,951	15,808
Stamet Pattimura	0,925	13,065

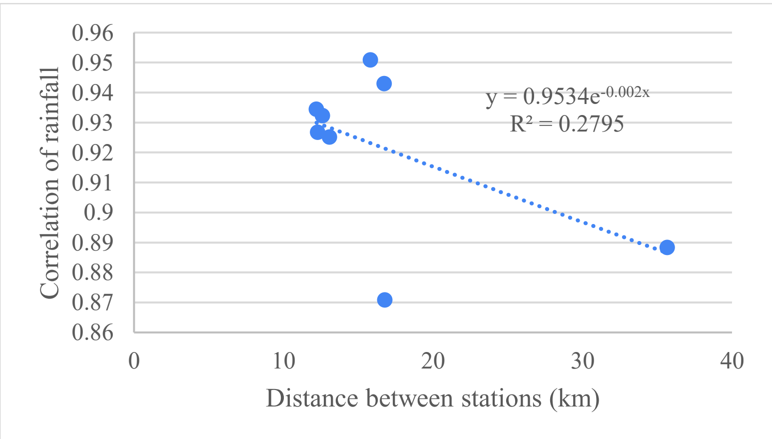

Figure 3. Exponential Curve Plot

Table 7. Coefficient of Variation of Annual Average Rainfall

Years	Xi	(Xi - $X_{rata-rata}$)^2
2014	2.278,31	1.453.025,32
2015	1.952,35	584.326,14
2016	2.772,61	7.685.489,29
2017	5.177,94	26.811.036,75
2018	3.462,98	11.992.195,85
2019	2.365,76	5.596.832,21
2020	4.198,16	17.624.568,38
2021	5.152,88	26.552.120,77
2022	4.390,21	19.273.965,80
2023	3.086,08	9.523.858,91
Total	**34.837,28**	**127.097.419,41**
Average	**3.483,73**	
SD	**1.187,94**	
CV	**0,34**	

Based on the exponential relationship modeling results shown in **Figure 3**, the initial correlation parameter was obtained as $r_0 = 0.9534$, characteristic distance $d_0 = 500$ km, and coefficient of determination $R^2 = 0.2795$. These parameters serve as the foundation for analyzing rain gauge network density.

The parameters r_0 and d_0 were derived from the exponential regression equation:

$$r(d) = r_0 \exp\left(-\frac{d}{d_0}\right) = 0.9534e^{-0.002d}$$

where $r_0 = 0.9534$ represents the theoretical correlation at zero distance ($d = 0$ km), and $d_0 = \frac{1}{0.002} = 500$ km represents the correlation radius.

The coefficient of variation (C_v) was calculated from the ratio of standard deviation (σ) to mean rainfall depth (μ):

$$C_v = \frac{\sigma}{\mu} = \frac{1{,}187.94}{3{,}483.73} = 0.34$$

Subsequently, the allowable averaging error (Z_1), interpolation error (Z_3), and ideal Kagan triangle spacing (L) were determined. The parameter Z_1 represents the allowable averaging error level, where smaller values demand higher accuracy and a greater number of stations (n). Meanwhile, Z_3 indicates the spatial interpolation error between stations.

For a study area $A = 768.15$ km^2 at a 3% allowable error level ($Z_1 = 3\%$, requiring $N = 7$ stations), the parameter calculations are expressed as follows:

$$Z_1 = C_v\sqrt{\frac{1-r_0}{N} + \frac{0.23 \cdot \sqrt{A}}{d_0 \cdot N^{1.5}}} = 0.34\sqrt{\frac{1-0.9534}{7} + \frac{0.23 \cdot \sqrt{768.15}}{500 \cdot 7^{1.5}}} \approx 0.03\ (3\%)$$

$$Z_3 = C_v\sqrt{\frac{1}{3}(1-r_0) + \frac{0.52 \cdot \sqrt{A}}{d_0 \cdot \sqrt{N}}} = 0.34\sqrt{\frac{1}{3}(1-0.9534) + \frac{0.52 \cdot \sqrt{768.15}}{500 \cdot \sqrt{7}}} \approx 0.1202\ (12.02\%)$$

$$L = 1.07\sqrt{\frac{A}{N}} = 1.07\sqrt{\frac{768.15}{7}} = 11.21 \text{ km}$$

Calculations were performed for allowable error levels of 1%, 2%, 3%, 4%, and 5%, and the resulting values for Z_1, Z_3, and L are presented in Table 8.

Table 8. Results of Z1, Z2, and L Calculations

N	Z_1	Z_3	L (km)
3	5	17,70	17,12
4	4	15,47	14,83
7	3	12,02	11,21
14	2	9,02	7,92
51	1	5,87	4,03

Based on Table 8, the Kagan–Rodda analysis results show that smaller allowable averaging error values (Z_1) require a greater number of rain gauge stations (N). This increase in the number of stations results in a shorter ideal spacing between stations (L) and a smaller spatial interpolation error (Z_3). Consequently, a denser rain gauge network enhances precision in representing the regional mean rainfall depth and improves rainfall estimation at unmonitored locations.

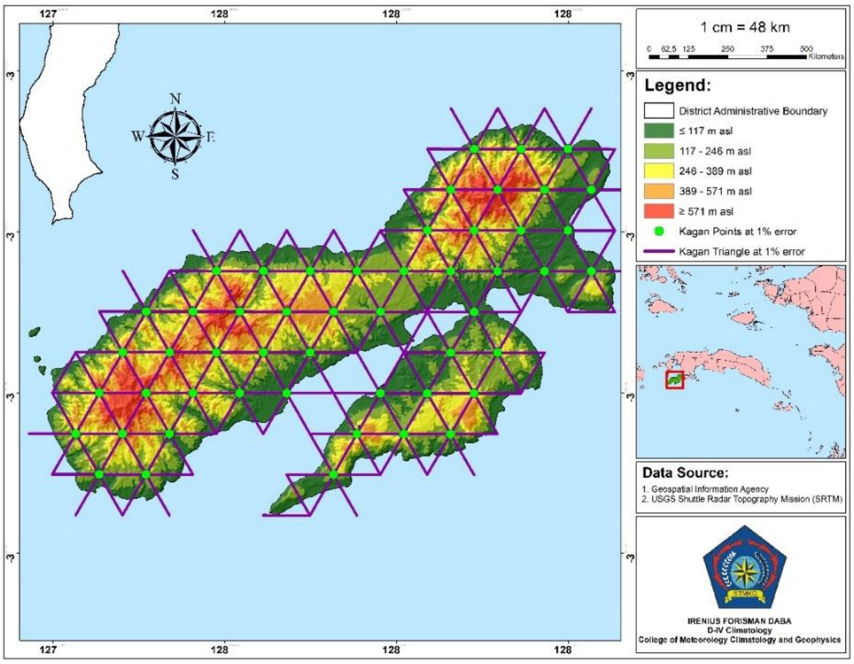

Figure 4. 1% Error Level

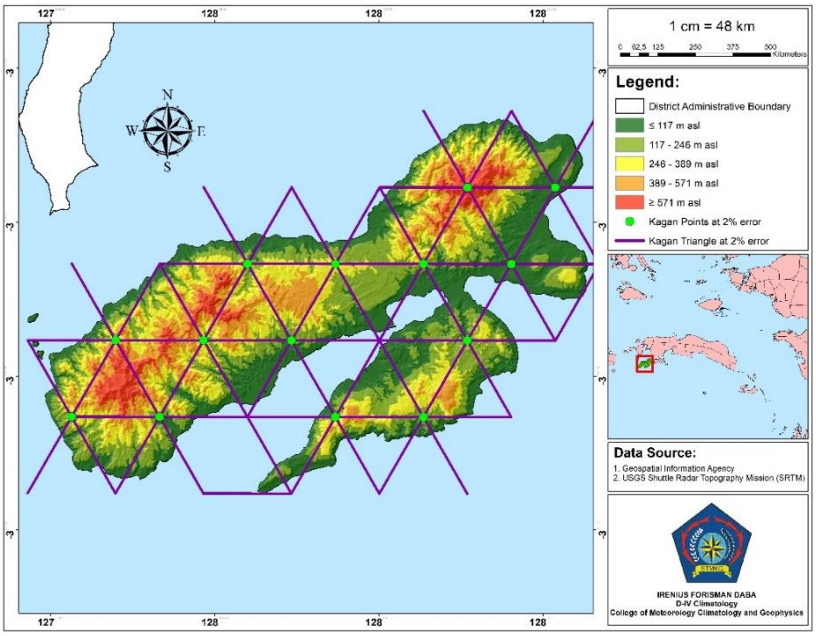

Figure 5. 2% Error Level

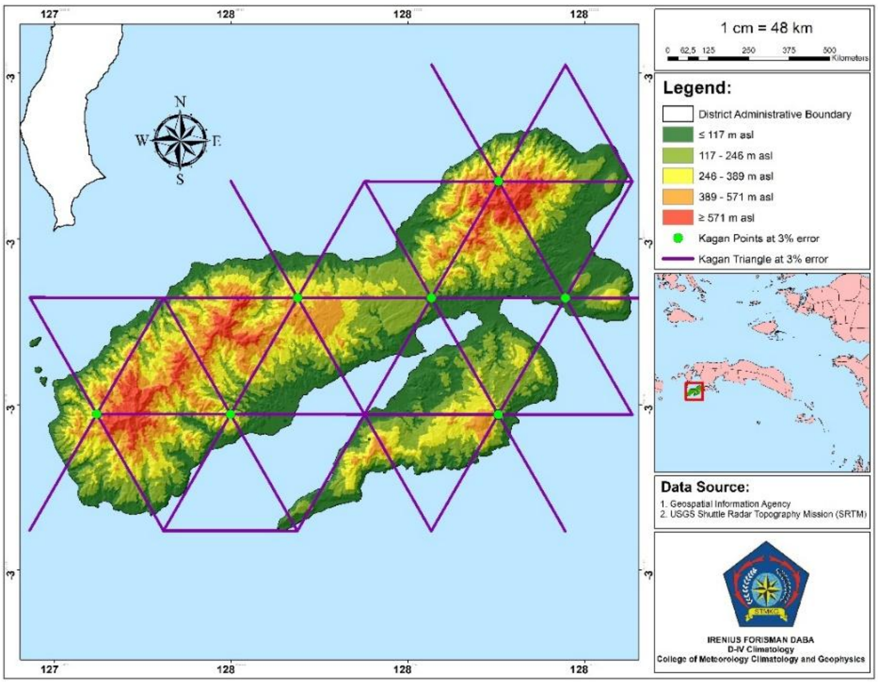

Figure 6. 3% Error Level

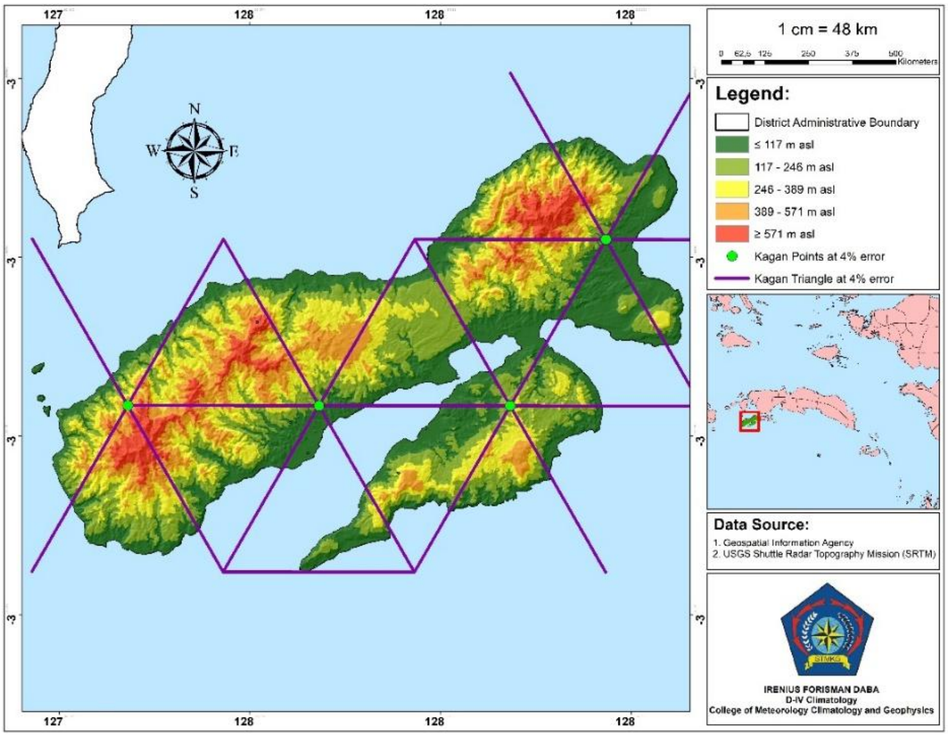

Figure 7. 4% Error Level

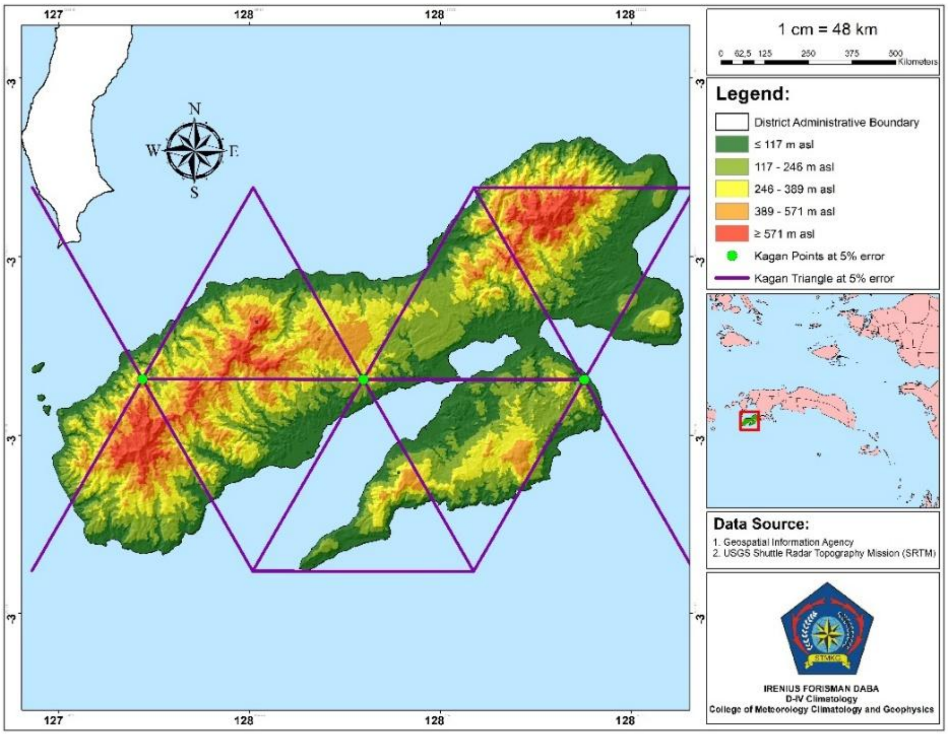

Figure 8. 5% Error Level

Based on the calculation results, the required number of rain gauge stations increases as the allowable error decreases. At an error level of 5% (Figure 8), 3 stations are required with an inter-station distance of approximately 17.12 km. At 4% (Figure 7) and 3% (Figure 6), the required number increases to 4 and 7 stations, with inter-station distances of 14.83 km and 11.21 km, respectively. For lower error levels of 2% (Figure 5) and 1% (Figure 4), the required number increases to 14 and 51 stations, with inter-station distances of 7.92 km and 4.03 km, respectively. These results indicate that lower allowable error levels require a greater number of rain gauge stations and shorter inter-station distances.

Discussion:

The results show that the required number of rain gauge stations increases as the allowable error decreases. At an allowable error of 5%, 3 stations are required, with an ideal spacing of 17.12 km, whereas at an allowable error of 1%, 51 stations are required, with an ideal spacing of 4.03 km. This pattern indicates that higher accuracy requires a greater number of stations and shorter inter-station distances. These findings are consistent with (Maulidiah & Darmawan, 2024), who demonstrated that network requirements based on the Kagan–Rodda method vary according to the specified error level. On Ambon Island, an allowable error of 3–5% results in a requirement of 3–7 stations, with an ideal spacing of 11.21–17.12 km, whereas an allowable error of 1–2% requires 14–51 stations, with an ideal spacing of 4.03–7.92 km. These results indicate that the Kagan–Rodda method provides a quantitative basis for determining the required number and ideal spacing of rain gauge stations according to the specified allowable error.

Implications:

These findings demonstrate that meeting network density criteria under WMO standards must be accompanied by spatial uniformity in station placement to adequately represent regional rainfall variability. A more representative network supports data availability for flood analysis and mitigation, reservoir and water resource management, food security and agricultural planning, the development of early warning systems for hydrometeorological events, and climate change adaptation planning. Thus, the evaluation results of the rain gauge network on Ambon Island can serve as a foundation for establishing priorities and requirements for network development based on local spatial conditions.

Research contribution:

This study contributes methodologically and practically by integrating the Thiessen polygon and Kagan–Rodda approaches to evaluate rain gauge network performance. It provides quantitative insights into the optimal number and spacing of rain gauge stations under varying error thresholds. The combined application of these methods offers a more comprehensive framework for network assessment compared to single-method approaches. Furthermore, the study delivers context-specific recommendations that are particularly relevant for small islands with complex mountainous terrain, thereby extending the applicability of rain gauge network design principles to underrepresented geographic settings.

Limitations:

Despite its contributions, this study has several limitations. The use of annual rainfall data reduces the ability to capture temporal variability, including seasonal fluctuations and extreme rainfall events, which are critical in hydrological assessments. Additionally, the analysis does not incorporate practical and logistical considerations such as site accessibility, installation constraints, maintenance costs, and local environmental conditions. These factors may significantly influence the feasibility of implementing the proposed network configuration. Therefore, the results should be interpreted as a theoretical optimization that requires further validation before practical application.

Suggestions:

Future research should incorporate higher temporal resolution data, such as monthly or daily rainfall observations, to better represent rainfall variability and improve the robustness of network design. Integrating topographic variables, such as elevation, slope, and orographic effects, would further enhance the spatial accuracy of rainfall estimation. Moreover, incorporating practical constraints, including accessibility, cost efficiency, and environmental suitability, is essential for developing implementable network designs. Field validation and pilot implementation studies are also recommended to evaluate the real-world performance of the proposed configurations and to refine the methodology for broader applications.

CONCLUSION

This study demonstrates that evaluating a rain gauge network depends not only on the number of stations but also requires considering spatial distribution, inter-station rainfall correlation, and estimation error levels. Integrating the Thiessen Polygon method, WMO density standards, and the Kagan–Rodda method provides an approach to evaluate the capability of the rain gauge network in representing rainfall variations on Ambon Island. This research provides insights into the relationship among inter-station distance, rainfall correlation, network density, and estimation error levels in small mountainous island environments. The findings show that network adequacy cannot be assessed solely based on the area covered by each station, but must also account for spatial rainfall characteristics. The Kagan–Rodda method offers a quantitative foundation for determining density requirements based on targeted precision.

Practically, these results can guide priorities for developing and optimizing the distribution of rain gauge stations on Ambon Island. A more representative network supports hydrological analysis, flood monitoring and mitigation, reservoir and water resource management, agricultural planning, early warning systems, and climate change adaptation. However, these analytical findings must be weighed alongside field conditions—such as accessibility, topography, site availability, and operational factors—prior to implementation. Future research should enhance this evaluation by using longer data periods, adding rain gauge stations, incorporating higher-resolution spatial data, and performing field validation at recommended locations. Furthermore, analyses could be extended to account for seasonal rainfall variations and extreme precipitation events to assess network performance across diverse hydrometeorological conditions.

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AUTHOR CONTRIBUTION STATEMENT

YD was responsible for conceptualizing and overseeing the study, developing the methodology, conducting formal analysis, and preparing the original draft. FD contributed to data curation, investigation, and the initial analysis. GMU assisted in methodology development, validation, and interpretation of results. WW contributed to data processing, visualization, and manuscript review and editing. All authors have read and approved the final version of the manuscript.

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