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Assessment of multiple spatial interpolation techniques for rainfall mapping in Ho Chi Minh City

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Abstract. Rainfall map plays a crucial role in describing the spatial distribution of rainfall from discrete rain gauge station data as input for water resource-related issues such as flooding, especially in large urban areas like Ho Chi Minh City. This research applied interpolation techniques in GIS to generate a rainfall map for Ho Chi Minh City. The research used three interpolation techniques including IDW, Spline, and Ordinary Kriging (OK), with two neighborhood points settings . The results illustrated that the interpolated rainfall maps varied depending on the interpolation techniques and two neighborhood points settings. IDW interpolation technique produced interpolated rainfall maps dependent on location and distance of the rain gauge stations. Meanwhile, Spline and OK techniques created rainfall with clearer spatial orientation and smoother rainfall variation. The values of R^2 (near 0), RMSE (>300 mm) and RSR (>1.0) indices indicated that all interpolation techniques generally have low numerical accuracy. This low predictive skill may be primarily attributed to the low density of the rain gauge network, given the complexity of the study area. The generation of spatial rainfall maps using these interpolation techniques in the study area requires careful consideration to ensure reliable results.

1. Introduction

Precipitation exhibits substantial spatial and temporal variability, and unlike continuous meteorological variables such as air temperature or pressure, its discontinuous characteristics complicate both interpolation and forecasting efforts [1]. High-quality precipitation information are essential for environmental research and constitute one of the most sensitive indicators of climate change [2]. This is considered as a challenge in tropical mountainous regions where rainfall variability strongly influences hydrological processes. Rainfall distribution is shaped by regional climatology, yet logistical constraints and the complexity of atmospheric interactions limit the deployment of reliable ground-based measurement systems [3]. The effective management of water resources depends on robust monitoring of climatic factors. Rain-gauge observations continue to serve as the primary source of information for most hydrological analyses, although the temporal resolution of these datasets varies depending on sensor technology and recording systems [4]. Hydrometric data more broadly are indispensable for the planning, operation, and management of water resources, including flood-defence strategies [5]. However, many regions still lack systematic meteorological monitoring networks and sufficiently dense surface hydrological observation systems, highlighting the need for coordinated improvements in environmental data collection.

Strengthening observational infrastructures not only increases measurement coverage but also enhances long-term data consistency. A substantial volume of high-quality climatic data is crucial to advancing scientific research and improving understanding of climate-change processes across multiple spatial scales [6]. Nevertheless, even where data exist, they are often fragmented, poorly archived, or difficult to access. Key gaps persist in understanding flow and sediment regimes, aquifer extents and recharge patterns, as well as present climate variability [7]. As climate extremes intensify, climate variables are increasingly integrated into vulnerability assessments to evaluate how different subsystems respond under severe weather conditions. Such assessments support urban planners in developing strategies to cope with extreme precipitation, improving infrastructure layout, and designing targeted industrial policies [8]. In many countries, however, the current observational networks remain inadequate. Similarly, although some regions maintain numerous weather observatories, the scarcity of long-term or continuous records limits the potential for scientific and agricultural applications. Moreover, analyses of critical climatic thresholds where points beyond which impacts may become severe that remain limited for many localities. Addressing these knowledge gaps forms an essential motivation for ongoing research efforts [9].

Geographic Information Systems (GIS) have evolved into a versatile platform capable of supporting a wide range of spatial applications. GIS enables precise localization of geographic features, thereby enhancing the ability of managers to monitor, utilize, and safeguard natural resources. Also, this tool also contributes to evaluating the impacts of both natural hazards and anthropogenic pressures such as climate change, rapid urban expansion, or environmental degradation, making it an essential tool for designing and implementing appropriate conservation strategies [10]. The analytical functions in GIS are critical for tasks like identifying drivers of land-use change, or evaluating the distribution of socio-economic or natural resources [11]. Given these capabilities, GIS has become one of the primary technologies for storing, processing, and visualizing geographically referenced data. These functions allow GIS to address spatial challenges with higher efficiency and accuracy. Integrating GIS with emerging technologies, such as advanced decision-making algorithms and real-time data systems, can substantially enhance the development of spatial decision-support systems, thereby improving their performance and relevance in complex planning and management contexts.

Spatial interpolation is a technique used to estimate values at locations where direct measurements are unavailable by relying on observations from nearby sites and, when appropriate, incorporating explanatory variables [12]. This approach is especially important in hydrological studies, as many regions have limited measurement networks. Rainfall stations in river basins are often sparsely and unevenly distributed, reducing the spatial representativeness of precipitation measurements. This poor coverage hinders the accuracy of flood forecasting, which relies heavily on continuous and reliable rainfall inputs [13]. As a result, spatial interpolation methods play a crucial role in transforming discrete rainfall observations into continuous rainfall surfaces; however, their effectiveness in basins with limited rain-gauge density still requires further evaluation.

Because interpolation methods comes with strengths and limitations depending on data characteristics including inverse-distance–based methods, multiple linear regression (MLR), artificial neural networks (ANN), and ordinary kriging (OK). Some of these approaches also incorporate a nearest-station search to improve accuracy [14]. The reliability of the generated rainfall surface ultimately depends on the quality of the interpolation technique used [15]. Moreover, interpolation outcomes are influenced not only by the chosen method but also by the selection of input stations [16]. Although radar- and satellite-based precipitation products have become increasingly important for analysing spatial rainfall patterns in regions with sparse gauge networks, these datasets often suffer from limitations such as coarse spatial resolution and relatively short historical records. Consequently, interpolation based on rain-gauge observations remains a necessary approach in many applications [17]. In general, interpolation techniques can be classified into deterministic and geostatistical categories. Deterministic methods generate continuous surfaces using rules based on similarity (e.g., inverse distance weighting, IDW) or smoothing (e.g., completely regularized spline, CRS). In contrast, geostatistical approaches—such as kriging and cokriging—make use of the statistical properties of the observed data to produce spatial predictions [2].

Therefore, the objectives of this research are (1) To generate rainfall mapping using several interpolation techniques (e.g., IDW, Spline, Kriging) in a study area; and (2) To assess accuracy of interpolated rainfall mapping.

2. Materials and methods

2.1 Study area and rainfall data collection

The study area is Ho Chi Minh City (HCMC), which is located in the transitional zone between Southeastern Vietnam and the Mekong Delta, with geographically from 10°10' to 10°38' N latitude and 106°22' to 106°54' E longitude (Figure 1). Covering an area of approximately 2,095 km^2, the city serves as the nation's primary economic hub [18]. This low-lying terrain renders the drainage system highly sensitive to tidal regimes and sea-level rise [18]. Climatologically, the study area belongs to the tropical climate zone with two distinct seasons including a rainy season from May to November and a dry season from December to April. The average annual temperature is approximately 27.9°C, with an average yearly precipitation of roughly 1,866 mm, the majority of which is concentrated during the monsoon months [19, 20]. For this study, yearly rainfall data during period 1993-2022 were collected from 13 rain gauge stations (Thu Duc, Tan Son Hoa, Cat Lai, Hoc Mon, Cu Chi, Pham Van Coi, An Phu, Binh Chanh, Le Minh Xuan, Tam Thon Hiep, Nha Be, Mac Dinh Chi, and Can Gio) (Figure 1). These rainfall data were provided by Southern Regional Hydrometeorological Center.

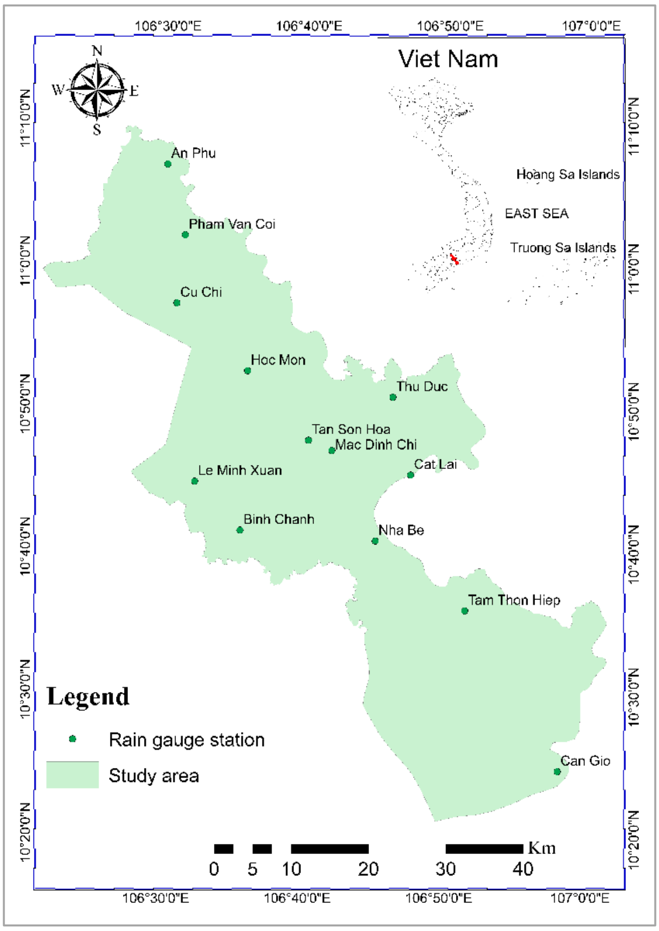

Figure 1. The study area with rain gauges locations.

2.2 *Interpolation techniques*

The research methodology is presented in Figure 2. Firstly, yearly rainfall data during period 1993–2022 of 13 stations were used to calculate mean annual rainfall for the whole period and 10 years mean annual rainfall during the period (1993-2022, 2003-2012 and 2013-2022). The division into three 10-year sub-periods aims to increase the sample size for a more robust accuracy assessment. Next, the calculated data were imported to spatial rain gauge locations data. After that, the spatial interpolation and mapping processes were performed using three interpolation techniques including (i) Inverse Distance Weighting (IDW) (Eq. 1) [21], (ii) Spline (Eq. 2) [22] and (iii) Ordinary Kriging (OK) (Eq. 3) [23]. These interpolation techniques were done with two neighborhood points settings (6 and 12 number of points). Other parameters for these interpolation techniques are illustrated in Figure 2 and were kept at their default settings. In order to assess these interpolation techniques, a Leave-One-Out Cross-Validation was employed [23]. Specifically, 12 rain gauge stations were selected from the collected rainfall dataset (13 stations) and used to interpolate for each interpolation technique for whole the study area. The remaining rain gauge station (1 station) was used to extract interpolated rainfall values and assess accuracy. This processes was repeated sequentially for 13 rain gauge stations and conducted separately for each analyzed period. Finally, the accuracy of the interpolation techniques was evaluated using four statistical indices (i) the Coefficient of Determination (R^2) (Eq. 4), (ii) the Root Mean Squared Error (RMSE) (Eq. 5), (iii) the RMSE-observations standard deviation ratio (RSR) (Eq. 6), and (iv) the Percent Bias PBIAS (Eq. 7) [24]. These statistical indices was calculated based on extracted values from the whole period and three 10-year sub-periods. These interpolations techniques were performed using ArcGIS software version 10.1.

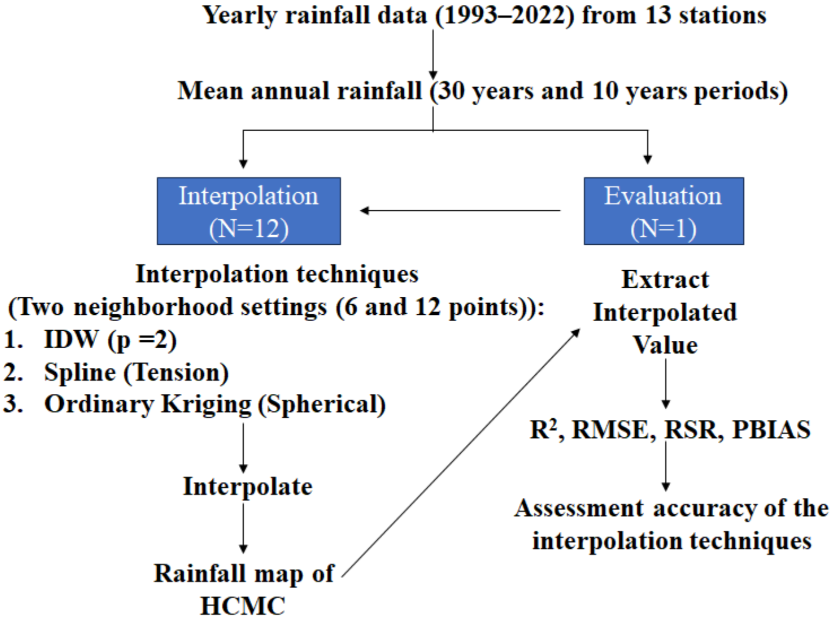

Figure 2. Research famework.

$$Z_0 = \frac{\sum_{i=1}^{S} Z_i \cdot \frac{1}{d_i^k}}{\sum_{i=1}^{S} \frac{1}{d_i^k}} \quad \text{(Eq. 1)}$$

Description:

Z_0: Estimated value at point 0

Z_i: The value z at control point i

d_i: Distance between point i and point 0

k: The larger the value of k, the greater the influence of neighboring points

S: The number of points S used

$$R(r) = \frac{1}{D\varphi^2}\left\{-\ln\left(\frac{r}{2D}\right) - c_E + \frac{1}{v-w}\left[wK_0\left(\frac{r}{D}\sqrt{v}\right) - vK_0\left(\frac{r}{D}\sqrt{w}\right) + \frac{w}{2}\ln v - \frac{v}{2}\ln w\right]\right\} \quad \text{(Eq. 2)}$$

with the auxiliary parameters v and w given by:

$$v = \frac{1}{2\tau^2}\left(1 + \sqrt{1 - 4\varphi^2\tau^2}\right), w = \frac{1}{2\tau^2}\left(1 - \sqrt{1 - 4\varphi^2\tau^2}\right)$$

From these definitions, the required condition for parameters φ and τ is:

$$1 - 4\varphi^2\tau^2 > 0$$

Description:

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r: the distance between the interpolated point and the sample point

φ: the tension parameter

τ: the generalized tension parameter

K_0: the modified Bessel function of the second kind

$c_E \approx 0.5772$: the Euler constant

D: the stiffness parameter

$$Z'(s) - m(s) = \sum_{i=1}^{N} \lambda_i [Z(S_i) - m(S_i)] \text{ (Eq. 3)}$$

Description:

S:Location for estimation

S_i: One of the nearby data locations

$m(s)$: Expected value of $Z(s)$

$m(S_i)$: Expected value of $Z(S_i)$

λ_i: Weighting factor

N: Number of sample data used for estimation

$$R^2 = \left[\frac{\sum_{i=1}^{n}(O_i - \bar{O})(P_i - \bar{P})}{\sqrt{\sum_{i=1}^{n}(O_i - \bar{O})^2}\sqrt{\sum_{i=1}^{n}(P_i - \bar{P})^2}} \right]^2 \text{ (Eq. 4)}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(O_i - P_i)^2} \text{ (Eq 5)}$$

$$RSR = \frac{RMSE}{STDEV_{obs}} = \frac{\sqrt{\sum_{i=1}^{n}(O_i - P_i)^2}}{\sqrt{\sum_{i=1}^{n}(O_i - \bar{O})^2}} \text{ (Eq. 6)}$$

$$PBIAS = \frac{\sum_{i=1}^{n}(O_i - P_i) \cdot 100}{\sum_{i=1}^{n} O_i} \text{ (Eq. 7)}$$

Where:

O_i: Observed rainfall value at station

P_i: Predicted (interpolated) rainfall value at station

$\bar{O}$: Mean of observed values;

$\bar{P}$: Mean of predicted values;

n: Total number of stations.

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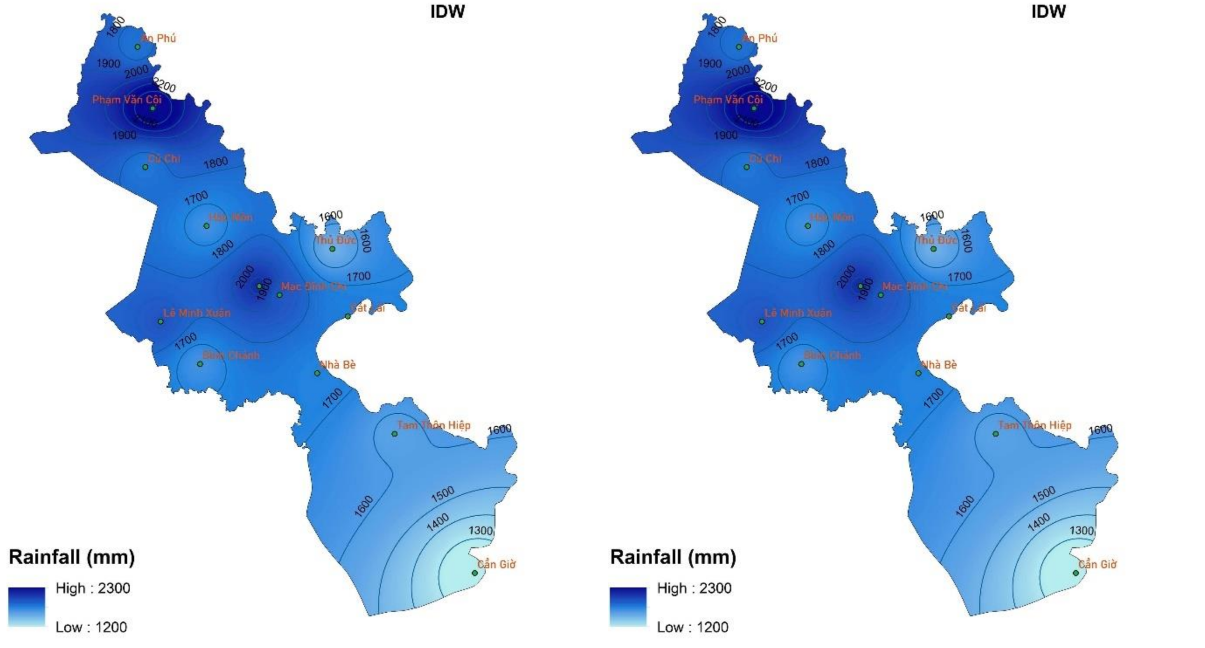
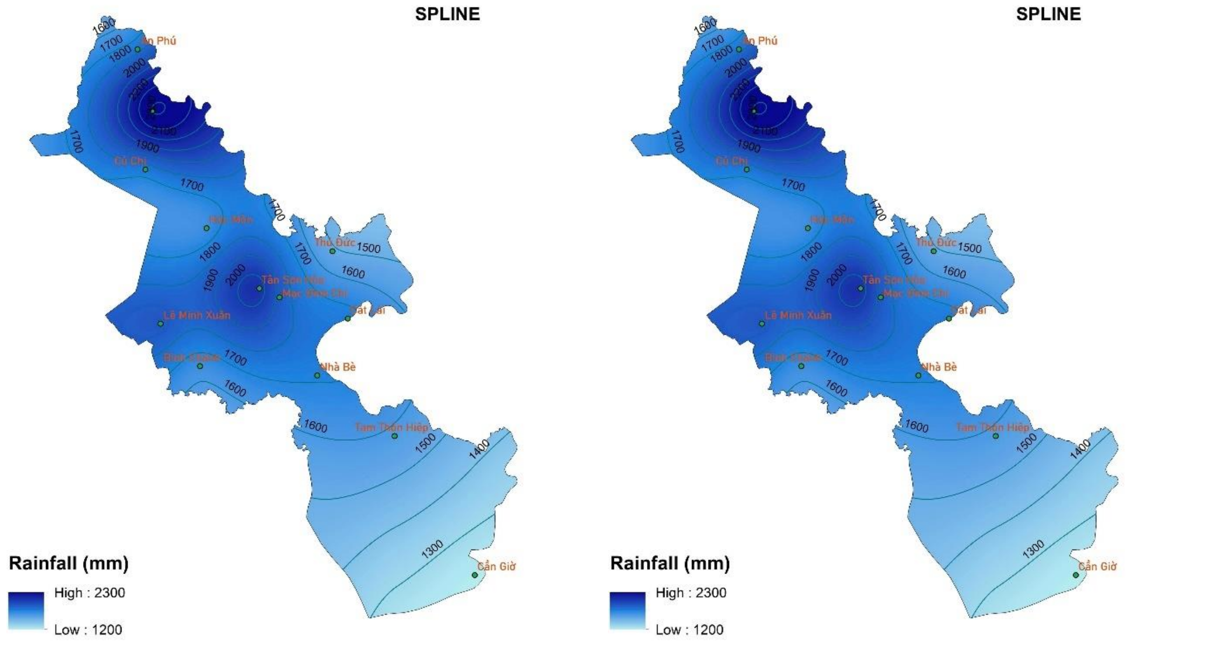
3. Results and discussion

3.1 Interpolated rainfall mapping
Interpolated maps of annual rainfall for HCMC over the 1993-2022 period using three interpolation techniques IDW, Spline, and OK are shown in Figures 3, 4 and 5. Overall, the interpolated results showed differences in spatial distribution of rainfall in the study area. The interpolated rainfall map by using the IDW technique showed that the distribution of rainfall is strongly influenced by location and distance to the rain gauge stations (Figure 3). Areas with high and low rainfall values generating around the rain gauge stations, particularly Pham Van Coi, Tan Son Hoa, and Mac Dinh Chi stations. This characteristic reflects algorithm of IDW, where the weight decreases with distance, causing the interpolated values to be strongly influenced by the nearest rain gauge stations. Therefore, the rainfall distribution exhibits a high degree of locality and lacks smooth transitions between areas located between different rainfall measurement stations. Meanwhile, the interpolated rainfall map based on the Spline interpolation technique showed a smoother and more continuous spatial distribution of rainfall across the study area (Figure 4). This technique constructed the rainfall distribution by minimizing overall curvature, thus creating a gradual transition between high and low rainfall gauge stations. The results showed that the rainfall distribution was decreasing from the North-Northwest (Cu Chi, An Phu) towards the South and Southeast (Can Gio), which consists with the climate and topography characteristics of HCMC. However, Spline technique tended to reduce extreme values, as evidenced by the less pronounced high rainfall centers compared to IDW and Kriging techniques. Besdie, the OK interpolation technique produced an interpolated rainfall map that both preserves high and low rainfall areas around the rain gauge stations and ensures spatial continuity by modeling the spatial correlation structure through a semivariogram (Figure 5). Areas of heavy rainfall are concentrated in the Northwest and central parts of the city (Pham Van Coi, Tan Son Hoa), while rainfall gradually decreases towards the South (Nha Be, Can Gio), reasonably reflecting the climatic trend of the coastal region. Unlike the IDW, the isohyetal lines of rainfall map using OK technique had a softer shape and clearer spatial orientation, showing the influence of the overall spatial structure rather than just relying on distance. The smoother rainfall variations observed in OK and Spline maps may partially reflect the mathematical smoothing properties of these algorithms rather than local rainfall gradients. However, the observed inland-to-coastal gradient (or North-South variation) in our maps is consistent with the established climatology of the Southern Vietnam monsoon, where rainfall is often influenced by the distance to the sea and urban heat island effects.



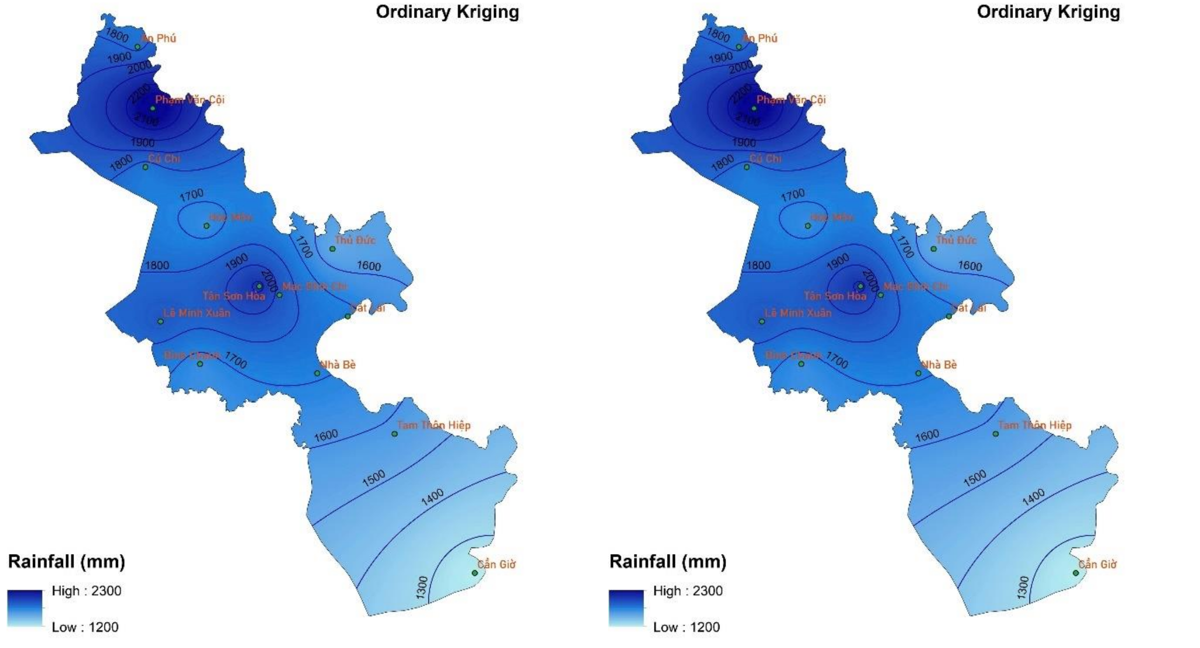
(a) (b)

Figure 3. Interpolated rainfall mapping using IDW technique with neighborhood 6 points (a) and 12 points (b) settings over the 1993-2022 period.



(a) (b)

Figure 4. Interpolated rainfall mapping using Spline technique with neighborhood 6 points (a) and 12 points (b) settings over the 1993-2022 period.



(a) (b)

Figure 5. Interpolated rainfall mapping using OK technique with neighborhood 6 (a) and 12 (b) points settings over the 1993-2022 period.

3.2 Accuracy assessment of the interpolated rainfall mapping

The accuracy assessment results of the interpolated rainfall maps varied depending on the techniques and two neighborhood points settings (Table 1). Regarding the R^2 coefficient, generally, all the interpolation techniques showed very weak correlations between measured and interpolated values. The IDW values were very low (0.0003 and 0.0064), indicating a weak correlation between interpolated and measured rainfall data (Figure 6). Similarly, the Spline technique showed almost no correlation between measured and interpolated values (Figure 7). However, the Spline technique showed improvement with R^2 of approximately 0.018–0.020. Meanwhile, OK had a higher R^2 value than IDW in 6 points (0.0148) and was particularly low in 12 points (0.0013), but also showed a very weak correlation between interpolation and measured data (Figure 8). The RMSE values for all techniques were greater than 300 mm (ranging from 313.9 to 447.5 mm), which significantly exceeds the optimal value. IDW with 12 points and OK with 6 points achieved relatively the best RMSE values (313.9 and 326.2 mm, respectively). Spline yielded the poorest results, with the highest RMSE value of 442.5 and 447.5 mm. Increasing the number of interpolation points from 6 to 12 did not significantly improve its accuracy. Regarding the RSR, the differences between the methods are more pronounced. IDW and OK have RSR values ranging from 1.1–1.2, significantly better than Spline (RSR = 1.6 for both neighborhood points settings). The lower RSR value reflects a smaller relative error, indicating that IDW and OK offer higher accuracy than Spline, with OK showing greater stability among the neighborhood points settings. In terms of PBIAS, all three techniques had negative values, suggesting a tendency to underestimate actual rainfall. However, OK had the smallest deviation (approximately −3.0% to

−3.1%), followed by IDW (−3.5% to −4.3%), while Spline had the largest deviation (approximately −5.6% to −5.7%). Thus, based on statistical indicators, OK demonstrates more stable and reliable performance compared to IDW and Spline.

While previous studies [25, 26, 27] reported high performance for the interpolation techniques, this study observed significantly lower numerical accuracy, characterized by low R2 values (near 0), high RMSE (>300 mm), and RSR values exceeding 1.0. These results indicated that the interpolation methods failed to provide reliable numerical estimates for the study area. This discrepancy is primarily driven by the sparsity of the rain gauge network, consisting of only 13 stations for the entire study area. As demonstrated in previous research [28, 29], rain gauge density significantly influences interpolation accuracy; low rain gauge density networks often lead to poor performance in both IDW and Kriging. In this case, the limited number of sampling points is insufficient to capture the high spatial heterogeneity and localized convective nature of tropical rainfall, resulting in the observed poor statistical indices.

Table 1. Statistical value of interpolation techniques.

Interpolation techniques		R^2	RMSE (mm)	RSR	PBIAS
IDW	6 points	0.0003	346.5	1.2	-3.5%
	12 points	0.0064	313.9	1.1	-4.3%
Spline	6 points	0.0198	442.5	1.6	-5.7%
	12 points	0.0179	447.5	1.6	-5.6%
OK	6 points	0.0148	326.2	1.1	-3.1%
	12 points	0.0013	331.8	1.2	-3.0%

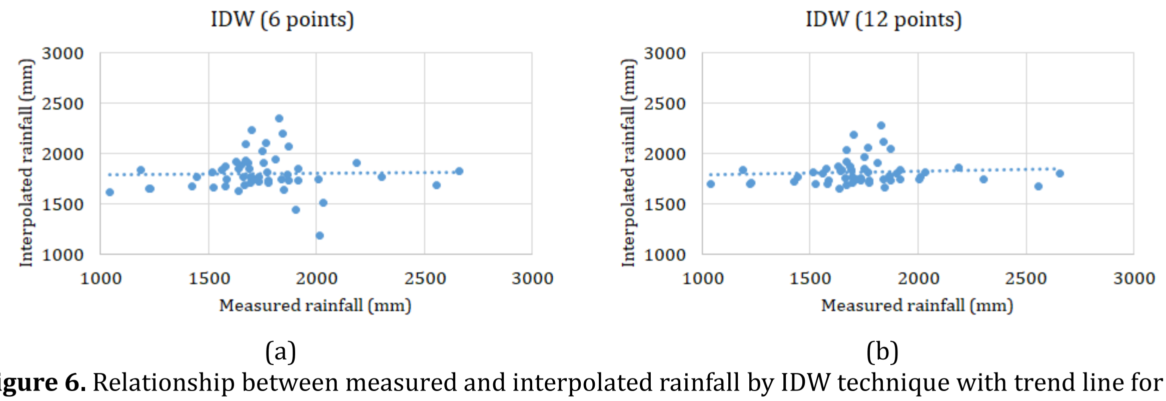


Figure 6. Relationship between measured and interpolated rainfall by IDW technique with trend line for neighborhood 6 (a) and 12 (b) points settings.

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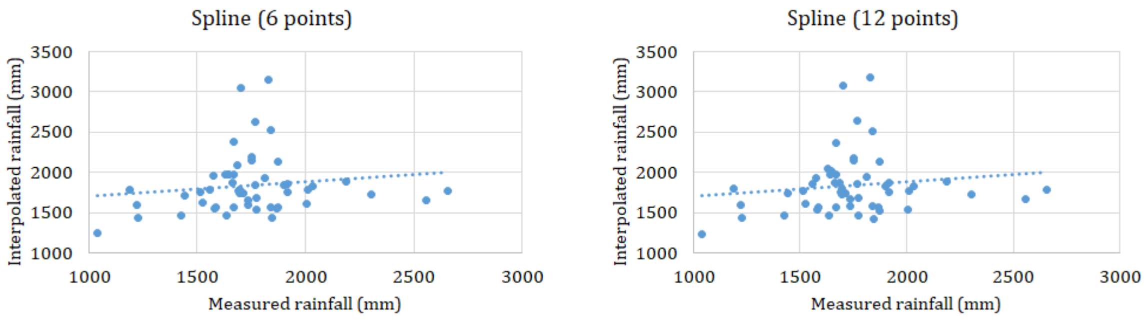
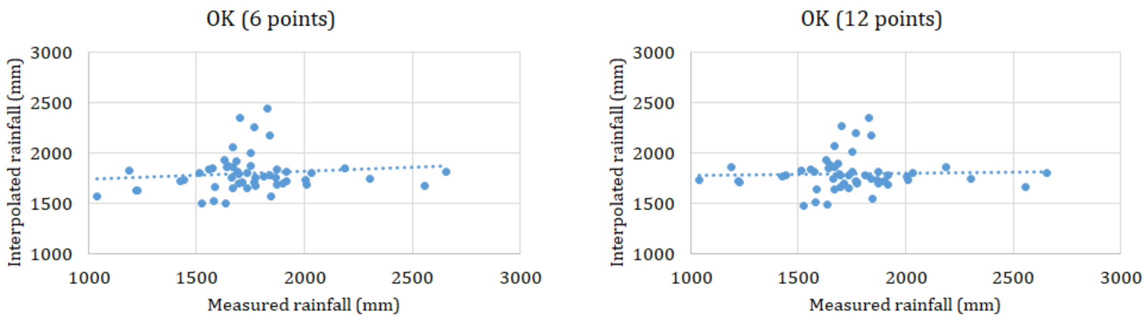


(a) (b)

Figure 7. Relationship between measured and interpolated rainfall by Spline technique with trend line for neighborhood 6 (a) and 12 (b) points settings.



(a) (b)

Figure 8. Relationship between measured and interpolated rainfall by OK technique with trend line for neighborhood 6 (a) and 12 (b) points settings.

4. Conclusions

This study evaluated three spatial interpolation techniques (IDW, Spline, and OK) with two neighborhood points settings for rainfall mapping in Ho Chi Minh City over the 1993–2022 period. The values of R^2(near 0), RMSE (>300 mm) and RSR (>1.0) indices indicated that all interpolation techniques generally have low numerical accuracy. This low predictive skill may be primarily attributed to the low density of the rain gauge network (13 stations), given the complexity of the urban area. IDW interpolation technique produced interpolated rainfall maps dependent on location and distance of the rain gauge stations. Meanwhile, Spline and OK techniques created rainfall with clearer spatial orientation and smoother rainfall variation. Thus, notable variations in spatial patterns were observed among the rainfall maps resulting from the three interpolation techniques. The generation of spatial rainfall maps using these interpolation techniques in the study area requires careful consideration (e.g., increasing station density and refining semivariogram models) to ensure reliable results. Future stuides should focus on integrating satellite-derived rainfall products or employing machine learning techniques with auxiliary environmental variables to improve spatial representation of rainfall in the study area.

Acknowledgement

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