Mapping Convective Precipitation Susceptibility in the Peñitas Watershed: A Novel Convectivity Index and Geostatistical Interpolation Framework

Dr. **Maritza ARGANIS**[*,1,2], M. Eng. **Margarita PRECIADO**[*,3], Dr. **Faustino DE LUNA**[1], Eng. Student **Cristian LÓPEZ**[1], Eng. Student **Edgar DE DIOS SEVILLA**[1], M. Eng. **Omar CABRERA**[1], Dr. **Rodrigo ROBLERO-HIDALGO**[3]

[1] Universidad Nacional Autónoma de México. Instituto de Ingeniería. Av. Universidad 3000 Ciudad Universitaria Edif 17 c.p. 04510 Coyoacán CDMX, México

[2] Universidad Nacional Autónoma de México. Facultad de Ingeniería. Av. Universidad 3000 Ciudad Universitaria c.p. 04510 Coyoacán CDMX, México

[3] Instituto Mexicano de Tecnología del Agua, Paseo Cuauhnáhuac 8532, c.p. 62550 Jiutepec, Mor., México

* MArganisJ@iingen.unam.mx; preciado@tlaloc.imta.mx

Abstract: *Convective precipitation poses significant hydrometeorological risks in the Peñitas River Basin, where short-duration, high-intensity rainfall events often trigger flash floods and landslides. This study introduces a novel empirical index—the Convectivity Factor (CF)—to spatially characterize convective susceptibility using high-frequency precipitation data from CFE's automated weather stations and topographic inputs from INEGI's Digital Elevation Model. The CF, defined as the ratio of maximum 1-hour to 24-hour precipitation, was calculated using annual historical maxima and mapped via three interpolation techniques: Inverse Distance Weighting (IDW), Kriging, and CoKriging. CoKriging, which incorporates elevation as a secondary variable, produced the most topographically coherent results. The resulting CF maps identify zones of elevated convective risk, supporting rainfall-runoff modeling and infrastructure planning in data-scarce regions. Though empirical, the CF provides a scalable tool for adaptive water management. Future research should integrate radar-derived instability indices and validate CF maps against observed extreme events.*

Keywords: *Convective precipitation, Convectivity factor, Spatial interpolation, Hydrometeorological risk, Rainfall-runoff modeling, CoKriging, Peñitas Watershed*

1. Introduction

Convective precipitation is a primary driver of hydrological extremes, particularly in vulnerable regions such as the Peñitas Watershed in southern Mexico. Localized and intense rainfall events frequently trigger flash floods, landslides, and severe soil erosion. These phenomena are becoming increasingly frequent and intense due to climate change, highlighting the urgent need for diagnostic tools that can spatially characterize convective susceptibility using high-resolution, accessible data sources [1-2].

A dramatic illustration of these risks occurred on the night of November 4, 2007, when a massive landslide released approximately 48 million cubic meters of rock and mud over an 80-hectare area. This event created a natural dam across the Grijalva River—one of Mexico's largest—between the Peñitas (downstream) and Malpaso (upstream) dams. The resulting barricade measured 80 meters in height, 800 meters in length, and 300 meters in width. The rural town of San Juan de Grijalva, situated along the riverbank, was devastated by the moving mass and the wave-induced flooding that followed. Tragically, 25 lives were lost. Using remote sensing and geographic information systems (GIS), this study contextualizes the landslide within the broader Grijalva River Watershed and links it to abnormal precipitation patterns observed in late October and early November 2007.

To address the need for spatial diagnostics of convective risk, this paper introduces the Convectivity Factor (CF)—a novel empirical index designed to map the annual frequency of convective events across the Peñitas Watershed. The CF integrates daily precipitation thresholds derived from the Comisión Federal de Electricidad (CFE)'s automated weather station reanalysis dataset. This approach offers a computationally efficient and scalable method for identifying regions prone to convective activity.

Although empirical, the CF provides a robust foundation for future enhancements in convective hazard diagnostics. Its reliance on open-access reanalysis data ensures broad applicability, especially in regions with sparse observational networks. By bridging the gap between large-scale climate datasets and localized hazard mapping, the CF contributes to adaptive strategies for managing convective risks in a changing climate.

Beyond climatological analysis, the CF has practical implications for hydrological modeling. CF maps support the estimation of design hyetographs—critical tools for rainfall-runoff simulations and hydraulic infrastructure planning. These maps are particularly valuable in data-scarce regions, enabling accurate modeling of short-duration rainfall events using daily records [3-4-5].

In areas with dense rainfall monitoring networks, CF maps enhance the regionalization of precipitation events and improve the reliability of hydrological models. In Mexico, Baeza (2007) [5] developed a Convectivity map that has been instrumental in estimating intensity-duration-frequency (IDF) relationships. Similarly, various authors [6-7] have advanced in hydrological modeling and water resources management through convection-based methodologies.

These efforts underscore the value of developing Convectivity maps in countries with extensive measurement networks, optimizing both planning and response to extreme hydrometeorological events.

In this paper, a Convectivity map for the Peñitas Watershed was developed by correlating maximum 1-hour precipitation with 24-hour totals. Nine automatic weather stations distributed across the basin provided precipitation records at 1-hour intervals. For each station, historical averages of maximum 1-hour and 24-hour precipitation were calculated, and the CF was derived accordingly. The Peñitas Watershed Digital Elevation Model (DEM), obtained from INEGI [8], was used as a reference for topographic adjustments.

Three interpolation methods were applied to generate this map:

Inverse Distance Weighting (IDW), Kriging and CoKriging, implemented in ArcGIS©, which also incorporated topographic data.

2. Methodology

This paper presents a robust framework for defining and mapping a novel Convectivity Factor (CF) across Peñitas Watershed, integrating reanalysis data, high-frequency precipitation records, and advanced spatial interpolation techniques.

2.1 Study Area

The Peñitas Watershed, located in southern Mexico, holds significant hydrological, ecological, and socio-economic importance. The Peñitas Dam, officially known as the Central Hidroeléctrica Ángel Albino Corzo, is a major hydroelectric facility on the lower Grijalva River. It has an installed capacity of 420 megawatts, contributing substantially to Mexico's renewable energy supply. This Riverbasin is situated in one of the rainiest regions of Mexico, making it highly susceptible to extreme precipitation and runoff. This dam plays a vital role in regulating water flow and mitigating flood risks, especially in downstream areas like Tabasco, which have experienced severe inundations during extreme weather events. Due to its high rainfall and complex terrain, the Peñitas Watershed is a hotspot for convective precipitation, making it a valuable case study for climate impact assessments and hydrological modeling. Events like the 2007 landslide and subsequent flooding underscore the basin's vulnerability to climate-driven hydrometeorological hazards. Flooding and landslides in the region have historically caused loss of life, displacement, and economic disruption, emphasizing the need for resilient infrastructure and early warning system [9].

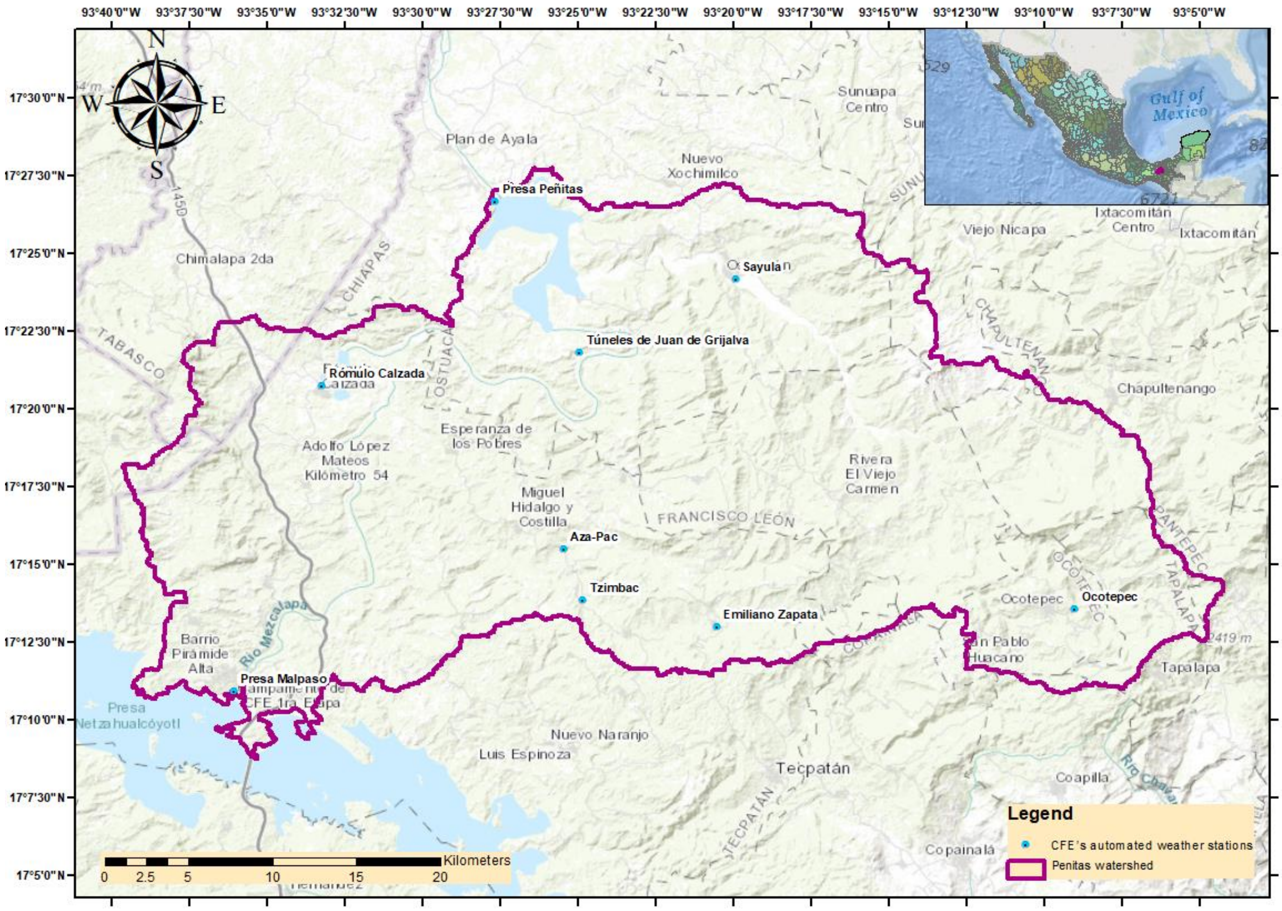

Fig. 1. Study site: Peñitas Watershed Location and their climatic Network. Source: Own design.

2.2 Data Sources

CFE's automated weather stations reanalysis Data: Daily maximum precipitation data from 2005 to 2025 year distributed across Peñitas Watershed provided 1-hour interval precipitation records, sufficient for calculating maximum 1-hour and 24-hour rainfall values.

Table 1: CFE's automated weather station's location and elevations. Source [10-11]

Automated weather stations name	Latitude	Longitude	Elevation Masl	Date
Aza-Pac	17.26	- 93.42	229.00	2005-09-06 to 2025-08-04
Emiliano Zapata	17.22	- 93.34	382.00	2005-09-06 to 2025-08-04
Presa Malpaso	17.18	- 93.60	200.00	2005-09-06 to 2025-08-04
Ocotepec	17.23	- 93.15	200.00	2005-09-06 to 2025-08-04
Peñitas Dam	17.44	- 93.46	53.00	2005-09-06 to 2025-08-04
Romulo Calzada	17.35	- 93.55	119.00	2005-09-06 to 2025-08-04
Sayula	17.40	- 93.33	51.00	2005-09-06 to 2025-08-04
Tuneles de Juan de Grijalva	17.36	- 93.42	123.00	2005-09-06 to 2025-08-04
Tzimbac	17.23	- 93.41	200.00	2005-09-06 to 2025-08-04

Digital Elevation Model (DEM): A 15x15 meters, download from INEGI [8] supporting topographic corrections and spatial interpolation.

2.3 Convectivity Factor Definition

A convective day was empirically defined a criterion:
- Daily precipitation > 0.1 mm

The Convectivity Factor (CF), also referred to as Factor R, is calculated as shown in equation 1 [5]:

$$R = \frac{P_{1h}}{P_{24h}} \tag{1}$$

Where:
- P_{1h}: Maximum 1-hour precipitation
- P_{24h}: Total 24-hour precipitation

This factor is valuable for estimating the intensity of short-duration rainfall from daily records, facilitating the development of design hyetographs for rainfall-runoff modeling and crucial for hydraulic infrastructure planning in data-scarce regions.

2.4 Procedure for Convectivity Factor Calculation

Procedure 1 was employed to obtain the Convectivity factor:
Procedure 1: Annual Historical Maxima from nine automated weather stations elected automatic stations set across Peñitas Watershed was utilized. For each station, the annual historical maximum 1-hour and 24-hour precipitation values were calculated and then averaged. The Convectivity factor for each station was subsequently determined using Equation (1).

2.5 Spatial Aggregation and Mapping

Daily convective flags were aggregated over 365 days to compute annual Convectivity frequency for each grid point. Resulting Convectivity map visually represents convective number days per year, generated using ArcGIS and Python-based visualization tools.
Spatial interpolations were performed using open-source software tools. Inverse Distance Weighting (IDW) and Kriging interpolations were applied in QGIS, while CoKriging was employed in ArcGIS©. Spatial interpolation generates raster cell values from known points, applicable to geographical variables like elevation or precipitation.
Inverse Distance Weighting (IDW): This deterministic technique assigns values to unsampled locations by averaging known values in their vicinity, with closer points exerting greater influence. It is widely used for its simplicity when spatial correlation structure is unknown. The IDW method general expression appears in equation 2.

$$z(x_0) = \frac{\sum_{i=1}^{n} \frac{Z(x_i)}{d(x_0,x_i)^p}}{\sum_{i=1}^{n} \frac{1}{d(x_0,x_i)^p}} \tag{2}$$

Where:
$z(x_0)$: Estimated value
$Z(x_i)$ Known values
$d(x_0, x_i)$: Distance between points
p: Power parameter controlling influence
This method is widely used for its simplicity and effectiveness in contexts where information on the spatial structure of the phenomenon is not available [12-14].
Kriging: A geostatistical technique that considers not only distance but also the spatial correlation structure modeled by a variogram. It provides an optimal and unbiased estimation under certain stationarity conditions, allowing for uncertainty prediction quantification. The simple Kriging basic form appears in equation 3.

$$Z^*(x) = m + \sum_{i=1}^{n} \lambda_i [Z(x_i) - m] \tag{3}$$

Where:
$Z^*(x)$ Estimated value
m Mean of the random field
λ_i. Weights from variogram equations

CoKriging: A Kriging extension of Esri [15] that incorporates auxiliary variables spatially correlated with the principal variable (in this case we applied elevation with precipitation) to enhance estimation accuracy, particularly with limited primary variable sampling. While more complex to implement, CoKriging can yield improved results when relevant auxiliary variables are available.
This method is ideal when sufficient information is available to model spatial dependence, and it allows for quantifying the uncertainty of predictions [16-17].
The ArcGIS program offers the option of adding complementary tools. In this case, Cokriging interpolation was considered, as this procedure allows for interpolation of functions of two or more variables. Specifically, in this analysis, it was important to consider the topography of the selected stations, so the interpolation was based not only on precipitation but also on station elevation. CoKriging interpolation is performed using equation 4.

$$\boldsymbol{Z^*(x) = \sum_{i=1}^{n} \lambda_i Z_1(x_i) + \sum_{j=1}^{m} \mu_j Z_2(x_j)} \quad (4)$$

Where:
$\boldsymbol{Z_1}$ Primary variable (precipitation)
$\boldsymbol{Z_2}$ Secondary variable (elevation)
$\boldsymbol{\lambda_i} y\ \boldsymbol{\mu_j}$. Weights from autocorrelation and cross-correlation
Although more complex to implement, CoKriging can offer better results when relevant auxiliary variables are available, such as altitude in precipitation studies [18]. CoKriging was implemented in ArcGIS©, enhancing spatial coherence by integrating topographic data.

3. Results and Discussion

This section presents the results derived from mapping the Convectivity factor (CF) across Peñitas Watershed using two distinct methodologies, followed by a comprehensive spatial patterns discussion, hydrometeorological implications, and the performance of various interpolation techniques. In Table 2 it can be observed calculated values for each station.

Table 2: CFE's automated weather station's results for Convectivity Factor

Automated weather stations name	R Convectivity Factor
Aza-Pac	0.53
Emiliano Zapata	0.51
Presa Malpaso	0.40
Ocotepec	0.57
Peñitas Dam	0.51
Romulo Calzada	0.57
Sayula	0.51
Tuneles de Juan de Grijalva	0.54
Tzimbac	0.54

It is worth noting that when spatial interpolation is performed at the national scale, the Convectivity map developed by Baeza (2007) indicates an approximate average value of 0.45 for the region encompassing the Peñitas Watershed. This value highlights the basin's pronounced susceptibility to convective precipitation, consistent with its location in one of the rainiest regions of Mexico.

3.1 Convectivity Factor Mapping: Procedure 1

Initial mapping of the Convectivity factor (CF), using the Inverse Distance Weighting (IDW) interpolation method and data from a sample of nine selected automated weather stations. The interpolation was performed using the Inverse Distance Weighting (IDW) method to capture regional variations in convective susceptibility. CF values were classified into three distinct ranges: low (green: 0.402–0.474), moderate (yellow: 0.475–0.529), and high (red: 0.530–0.571). These classifications delineate zones with varying degrees of convective activity, with red areas indicating elevated risk of convective precipitation events. This mapping provides a valuable tool for identifying regions potentially vulnerable to intense rainfall, flash flooding, and related hydrometeorological hazards.

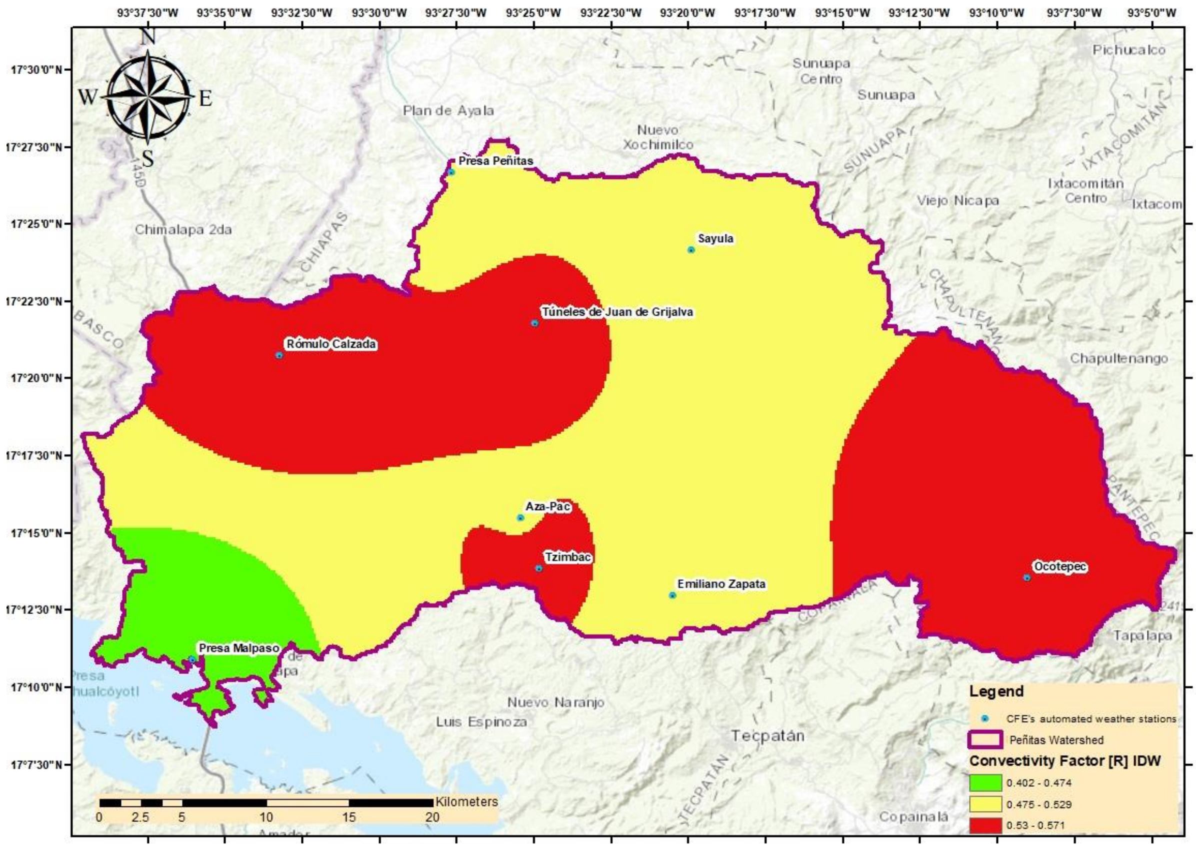

Fig. 2. Peñitas Watershed Convective factor map using IDW interpolation. Source: Own design

Figure 3 illustrates the spatial distribution of the Convectivity Factor (CF) across the Peñitas Watershed using the Kriging interpolation method. This geostatistical approach provides a more nuanced representation of spatial autocorrelation compared to deterministic methods like IDW. The CF values are categorized into three ranges: low (green: 0.402–0.474), moderate (yellow: 0.475–0.529), and high (red: 0.530–0.571), allowing for the identification of zones with varying convective potential. The map includes the boundaries of the Peñitas Watershed and the locations of CFE's automated weather stations, with key geographic references such as Presa Malpaso, Emiliano Zapata, and Tzimbac clearly labeled. The inclusion of a compass rose and coordinate grid ensures spatial orientation and georeferencing. Compared to the IDW-based map (Figure 2), the Kriging interpolation reveals smoother transitions and potentially more reliable estimates in areas with sparse data, enhancing the understanding of convective dynamics in the region.

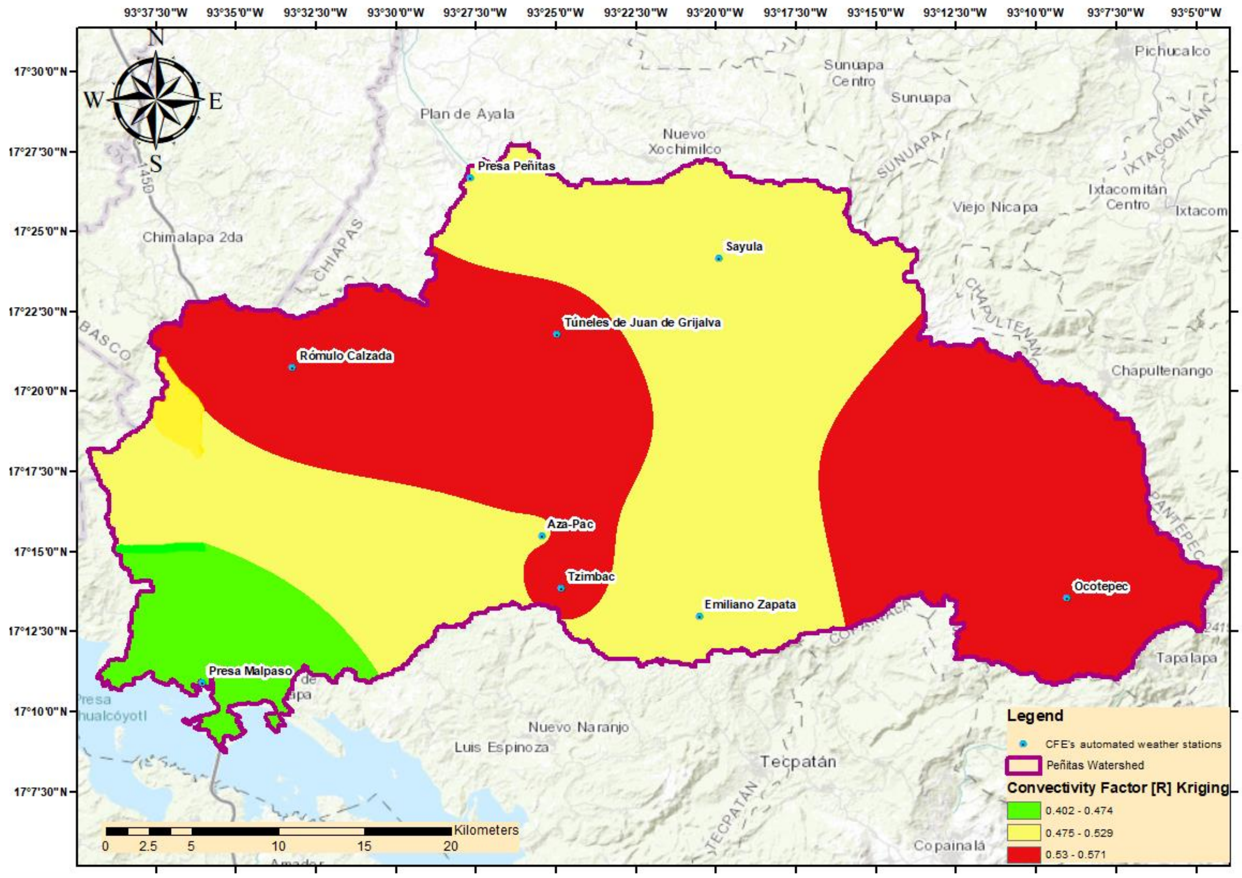

Fig. 3. Peñitas Watershed Convective factor map using Kriging interpolation. Source: Own design

Figure 4 displays the spatial distribution of the Convectivity Factor (CF) across the Peñitas Watershed using the Cokriging interpolation method, which integrates elevation as a secondary variable to enhance spatial prediction accuracy. By leveraging the covariance between CF and elevation, this geostatistical technique improves the interpolation in areas with limited primary data. The CF values are classified into three ranges—low (green: 0.402–0.474), moderate (yellow: 0.475–0.529), and high (red: 0.530–0.571)—highlighting zones with varying convective potential. The map includes the boundaries of the Peñitas Watershed (outlined in purple), the locations of CFE's automated weather stations (blue dots), and key geographic references such as Presa Peñitas, Sayula, and Ocotepec. Compared to IDW and Kriging methods, Cokriging offers a more refined spatial representation by accounting for topographic influence, which is particularly relevant in mountainous or elevation-sensitive region

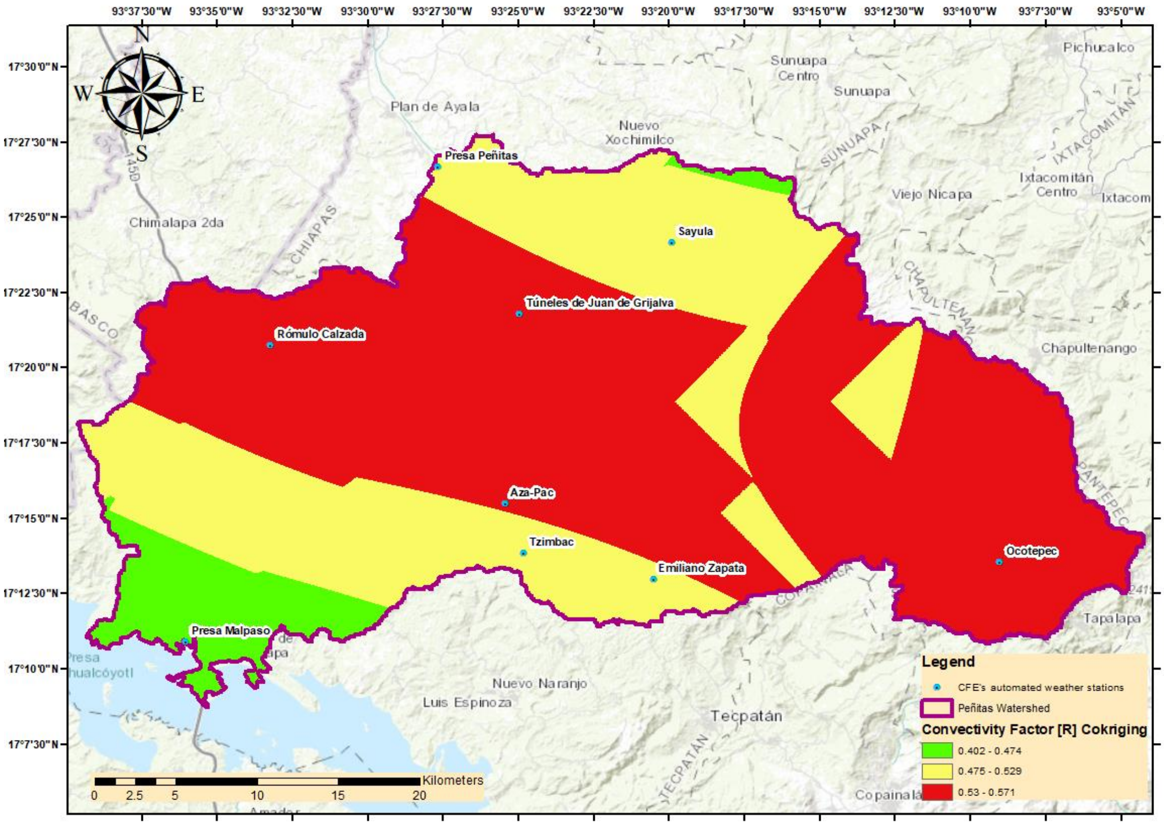

Fig. 4. Peñitas Watershed Convective factor map Cokriging interpolation. Source: Own design

3.2 Convectivity Spatial Patterns

The spatial distribution of the Convectivity Factor (CF) across the Peñitas Watershed reveals distinct regional patterns influenced by both meteorological inputs and topographic variability. Using three interpolation methods—IDW, Kriging, and Cokriging—the CF maps consistently identified zones of elevated convective activity concentrated in the central and southeastern portions of the basin. These areas, marked in red (CF > 0.530), suggest a higher likelihood of intense convective precipitation events. While IDW provided a straightforward visualization of CF gradients, Kriging offered smoother transitions and better spatial continuity, especially in regions with sparse data. The Cokriging method, incorporating elevation as a covariate, further refined the interpolation by capturing terrain-driven influences on convective dynamics. This approach revealed subtle shifts in CF hotspots, particularly in elevated zones where orographic effects may enhance convective processes. Overall, the spatial patterns suggest that Convectivity is not uniformly distributed across the basin, but rather modulated by a combination of atmospheric and geomorphological factors. These insights are critical for identifying vulnerable zones and guiding localized hydrometeorological assessments.

3.3 Convectivity and Hydrometeorological Risk

High Convectivity values are closely associated with increased hydrometeorological risk, particularly in regions prone to intense rainfall, flash flooding, and slope instability. The CF maps generated through spatial interpolation highlight several high-risk zones within the Peñitas Watershed, where convective activity exceeds critical thresholds.

Areas with CF values above 0.530—especially those identified through Cokriging—correspond to regions with steep terrain, limited drainage infrastructure, and historical records of extreme weather events. These zones are likely to experience rapid runoff, soil erosion, and potential landslides during convective storms. Moreover, the proximity of critical infrastructure, such as Presa Peñitas and Presa Malpaso, to high CF regions underscores the importance of integrating Convectivity analysis into reservoir management and emergency planning.

By linking Convectivity patterns with hydrometeorological hazards, this study provides a framework for proactive risk mitigation. The results support the development of early warning systems, targeted monitoring strategies, and adaptive land-use planning to reduce vulnerability and enhance resilience in the basin.

3.4 Limitations and Future Research

Despite the methodological robustness of the proposed Convectivity framework, several limitations warrant attention are explained below.
Regarding the data coverage constraints, the spatial interpolation relied on a limited number of automated weather stations, which may affect CF accuracy in underrepresented zones.
Temporal Aggregation Bias takes place because using annual historical maxima may obscure intra-annual variability and miss short-term convective anomalies.
While elevation was integrated via CoKriging, the 15×15 m DEM may not fully capture microtopographic influences on convective dynamics and that leads to a DEM Resolution Sensitivity.
The CF, while practical, lacks direct linkage to atmospheric instability indices such as CAPE or lifted index, limiting its physical interpretability.

Future Research Directions worth mentioning are described next.

Integration with Atmospheric Indices with the combination of CF with radar-derived convective parameters (e.g., CAPE, reflectivity) to enhance physical realism.
Multi-source Data Fusion with the Incorporation of satellite-based rainfall products (e.g., GPM, CHIRPS) to improve spatial resolution and temporal granularity.
Validation Against Extreme Events helped with Cross-reference CF hotspots with historical flood and landslide records to assess predictive reliability.
Machine Learning Enhancements with the exploration of hybrid models that fuse geostatistics with supervised learning for dynamic Convectivity mapping.

4. Conclusions

This paper presents a novel Convectivity index (CF) tailored to the Peñitas Watershed, offering a computationally efficient method for identifying regions prone to convective precipitation. By leveraging high-frequency rainfall data and integrating elevation through CoKriging, the resulting CF maps reveal spatial patterns aligned with known hydrometeorological risks.
The comparative analysis of IDW, Kriging, and CoKriging underscores the value of geostatistical methods in enhancing spatial coherence, particularly when auxiliary variables are available. The CF values—ranging from 0.40 to 0.57—suggest that a significant portion of daily rainfall is concentrated in short-duration events, reinforcing the need for refined hyetograph design and flood modeling.
While empirical, the CF framework provides a foundation for scalable hazard diagnostics and supports climate adaptation strategies in data-scarce regions. Future enhancements should focus on integrating atmospheric instability metrics, validating against observed events, and expanding the framework to other convective-prone basins.
The spatial patterns observed for 2021 year demonstrate strong contrasts that align with known climatological and hydrological risks in Peñitas Watershed. While empirical in nature, the Convectivity factor serves as a robust baseline for the continued development of advanced convective hazard diagnostics, particularly through the utilization of open reanalysis datasets. For future research, it is recommended to validate these maps against observed extreme events and to refine the treatment of stations with missing data to further enhance the estimations accuracy.

Acknowledgments

We would like to thank the Research and Development Secretariat of the Coordination of Scientific Research, UNAM, and the TUBs-UNAM project Validation of precipitation reanalysis products for rainfall-runoff modeling in Mexico (VIP MEXICO) for their support in carrying out this research.

References

[1] Purr, C., E. Brisson, and B. Ahrens. "Convective Rain Cell Characteristics and Scaling in Climate Projections for Peñitas Riverbasin." Geo-LEO, 2021.
[2] Perschke, M., B. Schmalz, and E. Ruiz Rodriguez. "Regional Analysis of Convective Heavy Rain Events in Hesse." EGUsphere, 2023.
[3] Bell, F. C. "Generalized Rainfall-Duration-Frequency Relationships." *Journal of Hydraulic Division*, ASCE 95 (1969): 311–327.
[4] Chen, C. L. "Rainfall Intensity-Duration-Frequency Formulas." *Journal of Hydraulic Engineering* 109, no. 11 (1983): 1603–1621. https://doi.org/10.1061/(ASCE)0733-9429(1983)109:12(1603).
[5] Baeza Ramírez, Carlos. *Regional estimation of convective factors for calculating intensity-duration-frequency relationships / Estimación regional de factores de convectividad para el cálculo de las relaciones intensidad-duración-frecuencia*. Master's Thesis. National Autonomous University of Mexico, 2007.
[6] Campos Aranda, D. F., and R. Gómez De Luna. "Procedure for obtaining intensity-duration-frequency curves from rainfall records." / "Procedimiento para la obtención de curvas intensidad-duración-frecuencia a partir de registros pluviométricos." *Tecnología y Ciencias del Agua* (May–Aug 1990): 39–52. https://revistatyca.org.mx/index.php/tyca/article/view/636/529.
[7] Domínguez Mora, R., E. Carrizosa-Elizondo, G. E. Fuentes-Mariles, M. L. Arganis-Juárez, J. Osnaya-Romero, and A. Galván-Torres. "Regional analysis for estimating design rainfall in the Mexican Republic"/ "Análisis regional para la estimación de precipitaciones de diseño en la República Mexicana." *Tecnología y Ciencias del Agua* 9, no. 1 (2018): 5–29. https://www.revistatyca.org.mx/index.php/tyca/article/view/1515.
[8] National Institute of Statistics and Geography / Instituto Nacional de Estadística y Geografía (INEGI). 2025. Available in: https://www.inegi.org.mx/.
[9] Federal Electricity Commission / Comisión Federal de Electricidad (CFE). "Extraction at Peñitas Dam Increases to Prioritize Population Safety; CFE Prepares for Rainy Season" / "Extracción en Presa Peñitas Aumenta para Privilegiar Seguridad de la Población; CFE se Prepara para Temporada de Lluvias." *Official Gazette / Boletín oficial*, May 3, 2022. https://app.cfe.mx/Aplicaciones/OTROS/Boletines/boletin?i=2512[1](https://app.cfe.mx/Aplicaciones/OTROS/Boletines/boletin?i=2512).
[10] Becerril Olivares, Mauricio. *Distributed parameter rainfall-runoff model for the Peñitas basin / Modelo de lluvia-escurrimiento de parámetros distribuidos para la cuenca Peñitas*. Master's Thesis. Postgraduate in Civil Engineering, UNAM, Mexico, 2016.
[11] National Water Commission / Comisión Nacional del Agua (CONAGUA). Southern Border Regional Management. CFE information requested from CONAGUA / Gerencia Regional Frontera Sur. Información de CFE solicitada a la CONAGUA. 2025.
[12] Shepard, D. "A Two-Dimensional Interpolation Function for Irregularly-Spaced Data." Paper presented at the 23rd ACM National Conference, Las Vegas, USA, August 27 - 29, 1968; 517–524. https://doi.org/10.1145/800186.810616.
[13] Panigrahi, N. "Inverse Distance Weight." In *Encyclopedia of Earth Sciences Series*, Springer, 2014. https://link.springer.com/content/pdf/10.1007/978-3-030-26050-7_166-1.pdf.
[14] Esri. "Interpolation methods using ArcGIS" / "Métodos de interpolación usando ArcGIS." ArcGIS Pro Documentation, 2025. https://pro.arcgis.com/es/pro-app/latest/tool-reference/spatial-analyst/comparing-interpolation-methods.htm.
[15] Esri. "ArcGIS Geostatistical Analyst: Inverse Distance Weighting." ArcGIS Pro Documentation, 2007. https://pro.arcgis.com/en/pro-app/latest/tool-reference/geostatistical-analyst/idw.htm.
[16] Ma, L., P. Wang, B. Song, X. Wang, and H. Dong. "An Efficient Kriging Modeling Method for High-Dimensional Design Problems Based on Maximal Information Coefficient." *Structural and Multidisciplinary Optimization* 61, no. 1 (2019): 39–57. https://doi.org/10.1007/s00158-019-02342-3.
[17] Krause, E., and K. Krivoruchko. "Kriging: An Introduction to Concepts and Applications." Esri User Conference Proceedings, 2018. https://proceedings.esri.com/library/userconf/proc18/tech-workshops/tw_1533-272.pdf.
[18] Dowd, P. A., and E. Pardo-Igúzquiza. "The Many Forms of Co-Kriging: A Diversity of Multivariate Spatial Estimators." *Mathematical Geosciences* 56 (2024): 387–413. https://doi.org/10.1007/s11004-023-10104-7.