Journal of Artificial Intelligence and Computing Applications (2026) 4(1): 40–47

MAIKRON

Journal of Artificial Intelligence and Computing Applications

Review article

Application of LSTM models and recurrent neural networks in flood detection using satellite images: a short narrative review

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ABSTRACT

The detection of floods using satellite imagery is essential for strengthening monitoring systems and early-warning mechanisms in vulnerable regions. This Short Narrative Review examines the effectiveness of Long Short-Term Memory (LSTM) models and other recurrent neural networks (RNNs) in comparison with traditional methods and deep learning architectures based on convolutional neural networks (CNNs). The reviewed studies indicate that CNNs remain the most widely used and report strong performance in the spatial segmentation of flooded areas, particularly with architectures such as U-Net and DeepLab. Moreover, some articles highlight that LSTMs provide advantages by integrating temporal information and hydrological variations that CNNs do not capture, which may support the interpretation of events with temporal dynamics. The most common limitations include environmental variability, sensor dependence, and lack of methodological consistency across studies. Although the evidence is still limited, the reviewed literature suggests that LSTMs may serve as a complementary approach for flood detection based on satellite imagery.

Keywords: flood detection, recurrent neural networks, long short-term memory

1. Introduction

In the field of applied artificial intelligence, Recurrent Neural Networks (RNNs) have become established as one of the most effective architectures for processing sequential data [1], enabling the modeling of complex temporal dynamics in natural phenomena and physical systems. Their ability to retain contextual information and learn long-term dependencies has driven their adoption across multiple areas of scientific computing [2], ranging from weather forecasting [3] to environmental monitoring [4]. Within this landscape, flood detection using satellite imagery has emerged as a high-impact field, where the automated analysis of time series is essential for anticipating extreme events and reducing human and material losses. In a global context marked by the intensification of hydrometeorological disasters, the integration of deep learning algorithms with Earth-observation technologies in optical and satellite radar sensors represents a promising pathway for strengthening early-warning systems and resilience to climate change.

Despite advances in deep learning applied to Earth observation, the automated detection of floods continues to face significant limitations in terms of accuracy, generalization, and scalability. Recent literature reveals that many traditional approaches, based on spectral

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https://doi.org/10.5281/zenodo.20802668

thresholds or supervised classification algorithms, exhibit inconsistent performance when confronted with the spatial and temporal variability of satellite data. Although RNNs and, in particular, Long Short-Term Memory (LSTM) models have demonstrated notable potential for capturing spatiotemporal relationships in image sequences, their application in flood detection remains fragmented and methodologically heterogeneous. This dispersion of approaches hinders the comparison of results and the consolidation of evaluation standards, creating a knowledge gap regarding the actual effectiveness of these architectures across diverse scenarios and under changing environmental conditions. In this context, it is necessary to conduct a critical and up-to-date review that synthesizes the most relevant findings and contributes to clarifying the role of RNNs and LSTM models in improving flood detection systems using satellite imagery.

In response to the identified limitations, this review aims to analyze and synthesize recent scientific evidence on the use of deep learning architectures for flood detection using satellite imagery, considering primarily convolutional neural networks (CNNs) based approaches, which are the most representative in the reviewed literature, and also incorporating studies that employ LSTM models and other RNNs when available. The analysis seeks to examine the predominant methodological approaches, the types of satellite data used, and the performance metrics reported, with the purpose of identifying patterns, strengths, and persistent gaps in the field. Under a Short Narrative Review framework, the study prioritizes both the analysis and the critical synthesis of high-quality research published over the past five years, guiding the discussion toward understanding how different architectures contribute to improving the accuracy and predictive capacity of early-warning systems. In this manner, the study is situated at the intersection of artificial intelligence, remote sensing, and climate-risk management, proposing an integrative perspective that fosters future applied research directions.

The review attains scientific relevance by demonstrating the lack of stable and comparable criteria in the methods used for flood detection through satellite imagery, particularly given the diversity of sensors, architectures, and validation strategies employed in recent literature. More than reiterating the potential of recurrent models, the central contribution of this work lies in clarifying the current state of this methodological heterogeneity and in assessing its impact on reproducibility, the generalization of results, and the operational capacity of hydrometeorological monitoring systems. By organizing and contrasting dispersed approaches, the review helps delineate actual advances, remaining challenges, and opportunities for standardizing analytical processes in future studies. In this way, it provides a conceptual foundation that guides the development of more consistent and useful research for integrating artificial intelligence techniques into flood-risk management.

To contextualize the scope of the analysis developed in the following sections, this article is structured in a manner consistent with the objectives of the review. Section 2, Methodology, details the procedure used for the identification, selection, and critical evaluation of the literature, specifying the criteria that allow for examining model performance, operational applicability, comparison among architectures, and geographic transferability. In Section 3, Thematic Overview, the main findings are presented, organized according to methodological trends, model types, and geospatial applications. Section 4, Discussion, provides an interpretative analysis that contrasts the results, identifies significant advances, and discusses persistent limitations in the field. Finally, Section 5, Conclusion, synthesizes the central contributions of the review and outlines research directions aimed at strengthening intelligent systems for flood detection.

2. Methodology

The methodology employed in this review aims to ensure a fair, transparent, and replicable process for the identification, selection, and analysis of the most relevant literature related to the topic of study. Google Scholar was used as the search engine due to its extensive repository of scientific articles and its accessible interface, which facilitates the retrieval of up-to-date academic sources. This platform is particularly useful for locating works from diverse disciplines, including the field of neural networks and machine learning, which constitute the main focus of our research.

The search was conducted using specific keywords: ("long short-term memory" OR "recurrent neural networks") AND satellite AND "flood detection", with the aim of encompassing the available literature related to the application of LSTM and RNN models in flood detection using satellite imagery. The search strategy was designed with clearly defined inclusion and exclusion criteria to ensure the quality and relevance of the selected articles.

Articles that met the following parameters were considered for inclusion:

Published in peer-reviewed scientific journals indexed in the Journal Citation Reports (JCR), specifically in Q1 or Q2 journals written in English. Published within the last five years, in order to include both foundational research and the most recent advancements. With a minimum of 10 citations per year, reflecting their impact and recognition within the scientific community.

In the identification phase, 636 records were obtained. After reviewing titles and abstracts, 592 records were excluded during the screening phase because they did not meet the initial relevance, language, or publication-type criteria. The remaining 44 articles were then evaluated in the eligibility phase according to the predefined quality criteria. At this stage, 33 articles were excluded: 12 were not classified as Q1 or Q2, and 21 had fewer than 10 citations per year. Ultimately, 11 articles met all the established parameters and were selected for inclusion. Any discrepancies were reviewed by a team of seven evaluators, with disagreements resolved through consensus.

Articles were excluded based on the following criteria: Not written in English ($n = 0$). Not directly related to the topic after reviewing the title and abstract ($n = 0$). Not indexed in the JCR or not meeting the required quality level ($n = 0$). Not classified as Q1 or Q2 ($n = 12$). Having fewer than 10 citations per year ($n = 21$).

The selection process illustrated in Figure 1 describes the systematic filtering from the initial search to the final inclusion of the studies. The selected articles were qualitatively analyzed to identify approaches, methodologies, and relevant findings on the use of LSTM and RNN networks in flood detection using satellite imagery.

To ensure the rigor of the identification process, the search was carried out in Google Scholar using the complete strategy: ("long short-term memory" OR "recurrent neural networks") AND satellite AND "flood detection", applying publication-year filters for the period 2020–2025. The query was conducted on January 15, 2025, and the results were cleaned through the manual removal of duplicates before proceeding to the initial screening. Subsequently, it was verified that each record met the methodological criteria previously described, thus forming the final set of selected studies. The articles that passed this process are presented in Table 1, where their main characteristics are synthesized to facilitate the subsequent comparative analysis.

3. Thematic Overview

The collection of analyzed studies focuses on the application of artificial intelligence and deep learning for advanced water-risk management, encompassing two essential lines of research: post-disaster event detection and mapping, and predictive monitoring or susceptibility mapping. In remote sensing-based flood detection, the predominant methodological approach is the implementation of CNNs for image classification and segmentation [6]. U-Net and its variants have become established as key tools for refining segmentation and improving mapping accuracy [11, 14]. Regarding data acquisition platforms and sensor types, the reviewed studies show a clear diversity of sources: some employ unmanned aerial vehicles (UAVs) equipped with RGB cameras to obtain high spatial resolution and rapid response in targeted areas [6], while others rely on SAR imagery, Sentinel-1 data, multisensor optical imagery, Very High Resolution (VHR) images, or Sentinel-2 multispectral data to ensure broader coverage and greater robustness under different environmental conditions [11, 14]. Complementarily, the predictive axis includes the integration of Artificial Intelligence of Things (AIoT) with in situ sensors for real-time overflow prevention [8], as well as machine learning models such as Random Forest (RF) for generating susceptibility maps based on topographic, hydrological, and environmental variables derived from satellite or GIS-based data [8, 15]. Based on the primary acquisition source reported in each study, SAR or Sentinel-1 imagery represents 36.4% of the reviewed articles, followed by satellite or GIS-derived environmental variables with 27.3%, optical VHR or Sentinel-2 multispectral imagery with 18.2%, UAV or RGB imagery with 9.1%, and AIoT or in situ sensing with 9.1%. This distribution, summarized in Figure 2, shows that the analyzed literature is dominated by satellite-based and geospatial data sources, while UAV and in situ sensing approaches are less frequent but operationally relevant.

In addition to the general trends observed, the comparative analysis reveals substantial methodological differences that affect both model performance and the comparability of results among studies. One of the most relevant divergences concerns the balance between spatial resolution and coverage extent. Some studies prioritize the high spatial resolution obtained through UAVs equipped with RGB cameras, which facilitates detailed flood characterization and damage assessment in localized areas [6]. In contrast, other studies rely on satellite sensors such as Sentinel-2, VHR, and SAR to ensure broader and more continuous regional observation, although generally with a lower level of spatial detail [11, 14]. At the algorithmic level, contrasts are also observed: Random Forest exhibits better generalization capacity in scenarios with significant geomorphological and climatic variability, particularly when environmental and topographic factors derived from satellite data are combined, whereas U-Net and related architectures are more strongly oriented toward fine spatial segmentation [15]. Similarly, the reviewed studies differ in their operational objectives, since most focus on post-disaster flood identification, while others adopt preventive approaches through AIoT-based systems and in situ sensors for real-time hydrological monitoring [8]. This methodological heterogeneity is especially relevant for assessing LSTM and RNN architectures, because their effectiveness depends on the availability of coherent multitemporal series with stable acquisition frequencies. Therefore, variability in spatial resolution, coverage, data availability, and evaluation protocols limits the possibility of directly comparing recurrent models with traditional spatial models or convolutional approaches.

The integrated analysis reveals that one of the most significant gaps in the literature is the lack of well-documented reference datasets, which hinders a rigorous evaluation of model performance and stability [10]. This deficiency limits the ability to compare approaches under homogeneous conditions and generates biases derived from differences in resolution, spatial extent, and atmospheric conditions, particularly affecting the transferability of the proposed methods [15]. At the methodological level, difficulties also persist in scenarios where the hydrological signal is subtle, such as spectrally homogeneous landscapes, or where events occur at very small scales [10], which restricts the generalization capacity of several architectures based on spatial segmentation. From a critical perspective, it is observed that

Table 1. List of analyzed articles on flood detection.

Title	Journal	Year	Reference
Deep Learning-Based Improved WCM Technique for Soil Moisture Retrieval with Satellite Images	Remote Sensing	2023	[5]
Uavs in disaster management: Application of integrated aerial imagery and convolutional neural network for flood detection	Sustainability	2021	[6]
Sentinel-1 SAR Images and Deep Learning for Water Body Mapping	Remote Sensing	2023	[7]
An Integrated Artificial Intelligence of Things Environment for River Flood Prevention	Sensors	2022	[8]
A Near-Real-Time Flood Detection Method Based on Deep Learning and SAR Images	Remote Sensing	2023	[9]
Flood Detection in Dual-Polarization SAR Images Based on Multi-Scale Deeplab Model	Remote Sensing	2022	[10]
Flood Detection Using Multiple Chinese Satellite Datasets during 2020 China Summer Floods	Remote Sensing	2021	[11]
Flood Susceptibility Assessment Using Artificial Neural Networks in Indonesia	Artificial Intelligence in Geosciences	2021	[12]
Flood Susceptibility Mapping Using Multi-Temporal Sentinel-1 Data and eXtreme Deep Learning Model	Geoscience Frontiers	2024	[13]
Mapping Pluvial Flood-Induced Damages with Multi-Sensor Optical Remote Sensing: A Transferable Approach	Remote Sensing	2023	[14]
Integrating Satellite Images and Machine Learning for Flood Prediction and Susceptibility Mapping for the Case of Amibara, Awash Basin, Ethiopia	Remote Sensing	2024	[15]

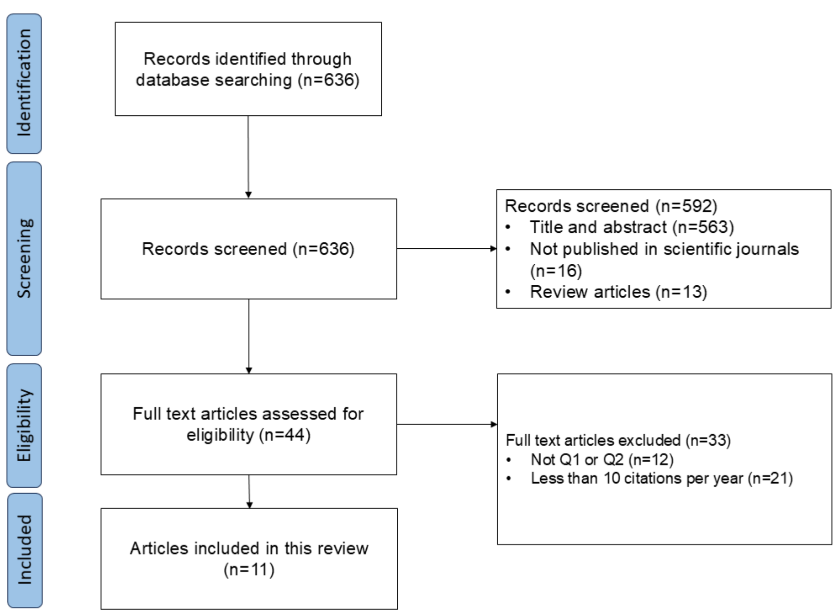

Figure 1. Flow diagram of the literature identification, selection, eligibility assessment, and inclusion process.

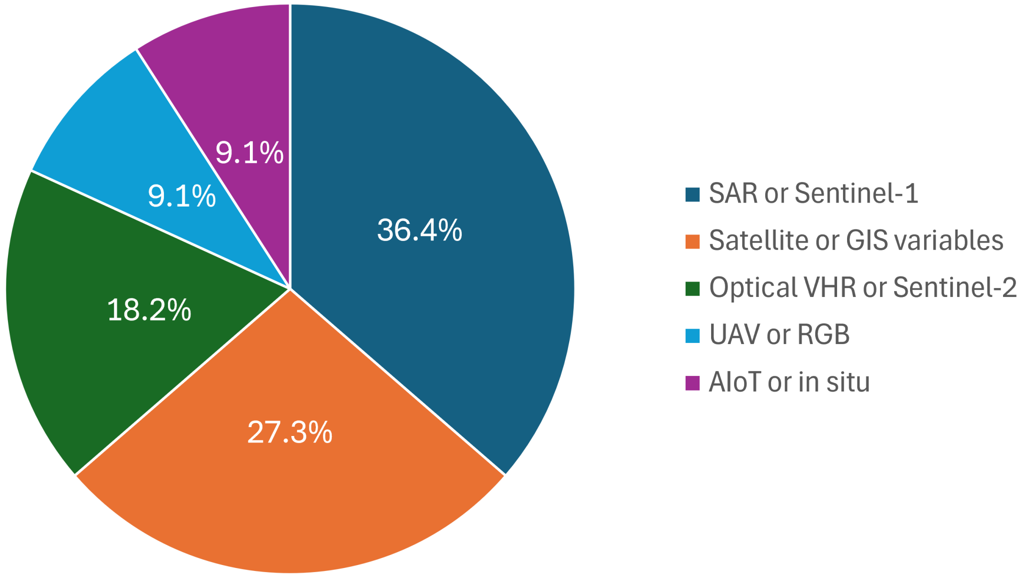

Figure 2. Distribution of the reviewed studies according to their primary acquisition platform or sensor type. The categories summarize the dominant data source reported in each article.

most of the reviewed studies emphasize techniques oriented toward spatial analysis, such as CNN, RF, or UAV sensors, whereas temporal approaches based on LSTM and RNN are constrained by the limited availability of consistent multitemporal series, making it difficult to properly contrast them with purely spatial models. This methodological imbalance suggests the need to promote more balanced experimental designs, as well as comparative frameworks that integrate both spatial and temporal information. In this regard, the integration of complementary sensors (radar, shortwave infrared) and the expansion of AIoT systems for continuous monitoring represent promising directions for generating more robust multitemporal datasets, a necessary condition for more accurately evaluating the real potential of recurrent architectures in flood detection.

4. Discussion

The evidence gathered shows a significant advance in the use of deep learning techniques for flood detection through satellite imagery; however, the methodological domain observed is strongly concentrated in convolutional architectures oriented toward spatial analysis. This predominance introduces a clear bias in the literature, as it limits the ability to fairly evaluate alternative approaches such as recurrent neural networks, including LSTMs, whose performance cannot be directly inferred due to the absence of rigorous comparative studies within the analyzed corpus. Thus, although recurrent models are theoretically suitable for representing the temporal evolution of hydrological variables, the review indicates that their practical application remains marginal and methodologically underexplored, which prevents the formulation of conclusive claims regarding their superiority or operational advantage. This lack of empirical evaluation is complemented by recurrent methodological limitations, data heterogeneity, scarcity of consistent multitemporal series, and the absence of comparable metrics that constrain critical analysis and hinder the generalization of the findings. In totality, these observations allow for a reinterpretation of the study's objective: rather than validating the performance of LSTM/RNN architectures, the results reveal a systematic gap in their implementation and evaluation, underscoring the need for research that jointly integrates temporal and spatial analysis to strengthen future monitoring and early warning systems.

The comparison of the study's findings with the analyzed articles reveals a clear methodological convergence, insofar as most investigations highlight the effectiveness of convolutional models and multisensor fusion strategies to improve accuracy in flood detection. This trend aligns with the high levels of accuracy reported in UAV-based applications [6], in SAR imagery from Sentinel-1 [9], in Copernicus program products, and in deep architectures such as U-Net or DeepLab [10], which demonstrate a notable capacity to process complex spatial information. However, a relevant divergence is observed regarding temporal approaches: although several studies employ historical data, multitemporal series, or continuous monitoring [13], the explicit application of RNNs or LSTMs is scarce, indicating a gap between the potential identified in the present study and current practices in the literature. Even so, the presence of spatiotemporal dynamics in the reviewed procedures suggests that the field is in a transitional phase toward more integrated approaches, which reinforces the theoretical relevance of recurrent models and their possible contribution to future research.

The results of the study show that CNNs continue to be the main theoretical reference in the literature due to their high performance in extracting spatial patterns, achieving reported accuracy values between 91% and 95% in flood detection tasks using well-established architectures such as U-Net or DeepLab [10]. (It should be noted that these values correspond to general performance metrics reported in the studies primarily accuracy and IoU which are not directly comparable across publications due to differences in datasets and experimental protocols.) Nevertheless, the increase in the availability of multitemporal series highlights the need to incorporate models capable of capturing temporal dependencies, such as LSTM and RNN architectures, whose theoretical benefits for modeling hydrological variability are not yet reflected in the reviewed literature. This absence reveals a methodological gap: although the studies work with sequential or multitemporal data, few employ recurrent approaches, which limits the exploitation of the dynamic component of flood processes. At the practical level, the use of UAVs stands out due to their ability to access hard to reach areas, reduce operational costs, and provide rapid and accurate detections [6]. Likewise, the integration of sensors such as Sentinel-1 and satellites from the Copernicus program expands geographic coverage [11], although with slight losses in spatial precision compared to very-high-resolution sensors. These approaches allow affected areas to be identified, soil moisture to be estimated, and water levels to be detected [5], thereby strengthening early warning systems. However, limitations persist, such as high computational requirements, sensitivity to atmospheric factors, and dependence on extensive and continuously updated databases. In summary, the methodological advances enrich the understanding of hydrometeorological processes and provide tools with a direct impact on risk management.

The limitations identified in the literature significantly affect the interpretation and scope of the results, as numerous studies depend on favorable environmental conditions and extensive datasets to ensure adequate performance. Factors such as variations in illumination, the presence of clouds, shadows, or watermarks introduce uncertainty that compromises the precise segmentation of flooded areas [7], weakening the internal validity of the models. Added to this is the reduced transferability to regions with different hydrological, topographic, or climatic characteristics, which restricts the generalization of the findings [14]. There also remains a lack of homogeneous methodological criteria both in the choice of sensors and in model design, which makes it difficult to rigorously compare approaches based on CNNs, LSTMs, or other deep learning architectures. Taken together, these limitations outline a scenario in which the effectiveness of the models depends closely on the quality of the available data, the geographic context, and the methodological consistency applied.

In totality, the evidence discussed demonstrates that the field of flood detection is moving toward more integrated approaches, where the combination of deep models, heterogeneous sensors, and multitemporal monitoring strategies constitutes the current axis of innovation. Although convolutional architectures continue to dominate due to their performance in spatial tasks, the gaps identified regarding the treatment of the temporal dimension reveal a clear opportunity for the systematic incorporation of recurrent models such as LSTM and RNN. At the same time, methodological limitations, particularly the lack of standardization, variability in data quality, and reduced geographic transferability introduce constraints that must be considered in any attempt at operational implementation. In this regard, the review offers a decisive contribution by clarifying the current state of the field, identifying its main gaps, and establishing the elements necessary to empirically strengthen future developments in monitoring and early warning systems.

5. Conclusion

The review shows that, although recurrent models and LSTM architectures possess theoretical potential for capturing relevant temporal dynamics in hydrological processes, CNNs and variants such as U-Net remain the predominant techniques due to their strong performance in spatial segmentation tasks. Likewise, the analyzed studies highlight the usefulness of UAVs for acquiring high-resolution imagery, the robustness of Sentinel-1 in complex atmospheric scenarios, and the improvements derived from multisensor integration. Cumulatively, these advances confirm the central role of deep learning in the rapid and accurate detection of floods; however, the limited adoption of recurrent models reveals a methodological gap that opens a clear avenue for future research aimed at systematically evaluating the contribution of RNNs and LSTMs in real operational contexts and with more demanding multitemporal datasets.

In light of the central objective of this work to examine the current and potential role of LSTM and RNN models in flood detection using satellite imagery the findings indicate that the contribution of these architectures remains incipient within the high-impact literature analyzed and still underrepresented in top-tier journals. Their limited adoption does not reflect a lack of theoretical relevance, but rather the absence of rigorous comparative studies that evaluate their usefulness against established models such as U-Net. In this regard, the review provides a conceptual clarification of where the temporal capabilities of recurrent models are actually positioned within the current methodological landscape, offering a more precise foundation to guide future research toward analytical frameworks that explicitly integrate the temporal and spatial dimensions of the flood phenomenon.

The findings of the review show that the integration of deep learning techniques with satellite sensors and UAV platforms constitutes an essential component for strengthening hydrometeorological risk management. The relevance of this approach responds to the increase in flood events and the need for more precise and operational tools. Nevertheless, limitations persist related to the dependence on large volumes of data, sensitivity to environmental conditions, and the limited generalization across regions with heterogeneous characteristics.

Taken together, the review makes it possible to more precisely delineate the incipient yet conceptually relevant role of LSTM models and other recurrent architectures within the current landscape of flood detection. Rather than offering definitive conclusions, the findings indicate the need for systematic comparative evaluations, reproducible experimental frameworks, and standardized multitemporal datasets that allow for rigorous measurement of the actual contribution of these models relative to well-established architectures such as U-Net. Based on this, several lines of future research are identified: (1) developing controlled studies that explicitly compare CNNs and LSTMs in operational scenarios; (2) expanding open repositories with high-quality temporal annotations; (3) designing hybrid approaches that integrate spatiotemporal dynamics within a single model; and (4) advancing toward unified methodological protocols that facilitate transferability across regions. These directions constitute necessary steps for consolidating the application of deep models in monitoring and early warning systems, contributing to a more robust and verifiable technological development.

Ethics Statement

This study did not involve human participants or animals and therefore did not require ethical approval.

CRediT authorship contribution statement

Christopher Abraham Arevalo-Erosa: Conceptualization, Methodology, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing, Visualization. **Jose Emilio Ek-Chay:** Conceptualization, Project administration, Supervision. **Rodrigo Kalel Rodriguez-Chavez:** Conceptualization, Project administration, Supervision. **Máximo Arturo Guzmán-Ascencio:** Conceptualization, Project administration, Supervision. **Raul Humberto Rodriguez-Mendez:** Conceptualization, Project administration, Supervision. **Romell Gerardo Mejia-Ramón:** Conceptualization, Project administration, Supervision. **Misael Garcia:** Conceptualization, Project administration, Supervision.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used ChatGPT to assist with language clarity and grammar correction. All final edits and intellectual content were determined and verified by the authors.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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