Physics-Informed Machine Learning for Extreme Rainfall Nowcasting: A Rapid Review Toward Sustainable Early Warning Systems

Gyslla Vasconcelos[1], Nayara Dornellas[1], Laisa Aguiar[1], Mariza Ferro[1]

[1]Institute of Computing – Universidade Federal Fluminense (UFF)
Av. Gal. Milton Tavares de Souza, S/Nº, São Domingos – Niterói – RJ – Brasil.

{gysllav, nayaradornelas, laisafonseca, mariza_ferro}@id.uff.br

Abstract. *Extreme rainfall nowcasting is essential for urban early warning systems, yet remains a challenging task. Data-driven machine learning models show promising performance but often suffer from limited generalization, physical inconsistency, and high computational cost. Physics-Informed Machine Learning (PIML) addresses these issues by integrating physical knowledge into learning algorithms. This paper presents a Rapid Review of PIML for extreme rainfall nowcasting, organizing integration strategies and addressing terminological fragmentation. The results reveal different levels of physical integration and limited focus on nowcasting. Most works neglect computational efficiency and resource-aware evaluation, highlighting challenges for developing reliable and sustainable nowcasting systems.*

1. Introduction

Extreme rainfall events have become increasingly frequent and intense in urban areas, causing severe social, economic, and environmental impacts [World Economic Forum 2025, Clark and Jaffrés 2025, Zhang et al. 2023, Porto et al. 2022, Fonseca et al. 2022]. In cities such as Rio de Janeiro, heavy precipitation is often associated with floods and landslides, exacerbated by complex topography, high urban density, and socio-environmental vulnerability [Migliani 2025, Dereczynski et al. 2017, Pristo et al. 2018]. In this context, short-term weather prediction, known as nowcasting, plays a critical role in early warning systems by supporting timely decision-making and risk mitigation actions [Brum et al. 2025, Porto et al. 2022].

Several approaches have been proposed for rainfall prediction. Numerical Weather Prediction (NWP) models remain the backbone of operational forecasting; however, accurately predicting extreme rainfall at high spatial resolutions, particularly in urban environments, remains challenging [Li et al. 2025, Frnda et al. 2022]. The chaotic and multiscale nature of atmospheric processes, combined with uncertainties in initial conditions and high computational costs, limits the effectiveness of traditional physics-based models in nowcasting scenarios [Brum et al. 2025, de Vasconcelos 2017].

Recent advances in Machine Learning (ML), particularly Deep Learning (DL), have shown promising results for precipitation prediction across multiple temporal scales, including nowcasting [Li et al. 2025, da Silva et al. 2025, Hsu et al. 2024, Ma et al. 2023, Frnda et al. 2022, Ravuri et al. 2021]. However, purely data-driven models often face limitations such as limited generalization, dependence on large volumes of data, and physically inconsistent predictions [Zhang et al. 2023, Kurth et al. 2023, Ta Gia et al. 2025, Li et al. 2024]. In addition, complex DL architectures may increase training time, energy consumption, and carbon footprint, raising concerns about their sustainability in real-time early warning systems [Breder et al. 2025, Brum et al. 2025, Porto et al. 2022].

In this context, Physics-Informed Machine Learning (PIML) has emerged as a promising paradigm to address these limitations by integrating physical knowledge into ML models. By incorporating physical constraints, governing equations, or physically meaningful features into the learning process, PIML aims to improve generalization, physical consistency, and computational efficiency. These characteristics are particularly relevant for extreme event prediction and align with the principles of sustainable and Green AI [Karpatne et al. 2017, Zhang et al. 2023, Kurth et al. 2023, Ta Gia et al. 2025, Li et al. 2024].

Despite recent advances, the application of PIML to extreme rainfall nowcasting remains fragmented and insufficiently systematized. Existing studies adopt heterogeneous terminology, modeling strategies, and levels of physical integration, making comparison and practical adoption difficult. Therefore, this paper presents a Rapid Review of PIML applied to extreme rainfall nowcasting. The study maps existing models and frameworks, analyzes strategies for incorporating physical knowledge, and highlights research gaps and open challenges, supporting the development of more reliable and sustainable nowcasting systems.

2. Theoretical Background

According to the World Meteorological Organization (WMO), extreme weather events are rare occurrences located at the tails of the statistical distribution of meteorological variables relative to local climatology [World Meteorological Organization 2023]. In this study, precipitation is used in a general climatological sense, while rainfall refers specifically to liquid precipitation associated with impacts in urban environments.

Extreme rainfall events are particularly critical in urban areas due to their impacts on populations and infrastructure [World Economic Forum 2025, Zhang et al. 2023, da Silva et al. 2022]. In cities such as Rio de Janeiro, short-duration and high-intensity rainfall is strongly associated with floods and landslides, especially due to complex topography, coastal conditions, and land-sea interactions, which increase convective rainfall and spatial variability [Migliani 2025, Pristo et al. 2018, Dereczynski et al. 2017]. These characteristics make accurate prediction at fine spatial and temporal scales particularly challenging.

Extreme rainfall events are associated with the tail of rainfall distributions and commonly characterized by short-duration, high-intensity accumulations [da Silva et al. 2022, Camuffo et al. 2020]. In operational contexts, impact-based thresholds are often adopted; for example, the Alerta Rio system defines extreme rainfall as hourly accumulations equal to or exceeding 50 mm [Sistema Alerta Rio 2025]. These events highlight the importance of accurate short-term prediction methods. In this context, nowcasting refers to very short-term weather prediction, usually ranging from minutes to a few hours ahead [Liu et al. 2025, Nerini et al. 2019]. Due to the highly localized and rapidly evolving nature of extreme rainfall, nowcasting remains particularly challenging under strict temporal and computational constraints [Brum et al. 2025, Zhang et al. 2023].

Recent advances in ML, particularly DL, have improved precipitation prediction by capturing complex spatiotemporal patterns from radar and satellite data [Li et al. 2025, Hsu et al. 2024, Ravuri et al. 2021]. However, data-driven models often require large datasets, exhibit limited generalization, and may produce physically inconsistent predictions [Zhang et al. 2023, Kurth et al. 2023]. In addition, DL models are computationally intensive, raising concerns about efficiency and sustainability in real-time applications [Breder et al. 2025, Brum et al. 2025].

To address these limitations, PIML integrates physical knowledge into ML models through strategies such as physical constraints, governing equations, hybrid models, and physics-aware architectures [Karpatne et al. 2017, Kashinath et al. 2021, Hao et al. 2023]. These approaches aim to improve generalization and physical consistency while potentially reducing computational costs [Breder et al. 2025, Brum et al. 2025]. However, PIML applications in extreme rainfall nowcasting remain fragmented, with heterogeneous terminology and varying levels of physical integration, motivating the Rapid Review presented in this work.

3. Research Methodology

This study adopts a Rapid Review (RR) methodology [Cartaxo et al. 2020] to map and systematize the state of the art of PIML applied to extreme rainfall nowcasting. The review focuses on a qualitative synthesis of models, integration strategies, and reported research gaps, following established guidelines for systematic reviews in software engineering [Petersen et al. 2015, Kitchenham and Charters 2007].

The study is guided by the following research questions:

- **RQ1.** Which PIML models and strategies have been applied to extreme rainfall nowcasting?
- **RQ2.** What challenges and research gaps are reported in the literature?

To ensure consistency between the research questions and the search strategy, the review protocol followed established guidelines for systematic reviews in software engineering [Kitchenham and Charters 2007].

A structured search strategy was defined based on three dimensions: (i) extreme rainfall events, (ii) nowcasting and short-term forecasting, and (iii) physics-informed or hybrid machine learning approaches. The search string was applied to the title, abstract, and keywords in the Scopus, Web of Science, and IEEE Xplore databases. IEEE Xplore was maintained to improve coverage of recent conference papers and emerging PIML approaches. The complete search strings and supplementary materials are publicly available in the replication package [de Vasconcelos 2026].

Given the evolving nature of PIML in extreme rainfall nowcasting, the search process was conducted iteratively to identify alternative terms and improve search sensitivity and specificity. The study selection followed a two-stage process combining automated database filtering and manual screening. Initially, studies were retrieved using the defined search terms and basic filters. Then, titles and abstracts were screened to assess relevance, followed by full-text evaluation of selected studies. Complementary identification of relevant studies was performed through citation tracking and exploratory searches to capture influential or emerging works not retrieved in the structured search.

For each selected study, key information was extracted, including the PIML approach, type of physical knowledge incorporated, data sources, forecast horizon, spatial resolution, and reported advantages and limitations. The analysis was conducted through qualitative synthesis, focusing on the comparison of models, physical integration strategies, and reported limitations. The overall process followed the PRISMA 2020 guidelines [Page et al. 2021], and is summarized in Figure 1.

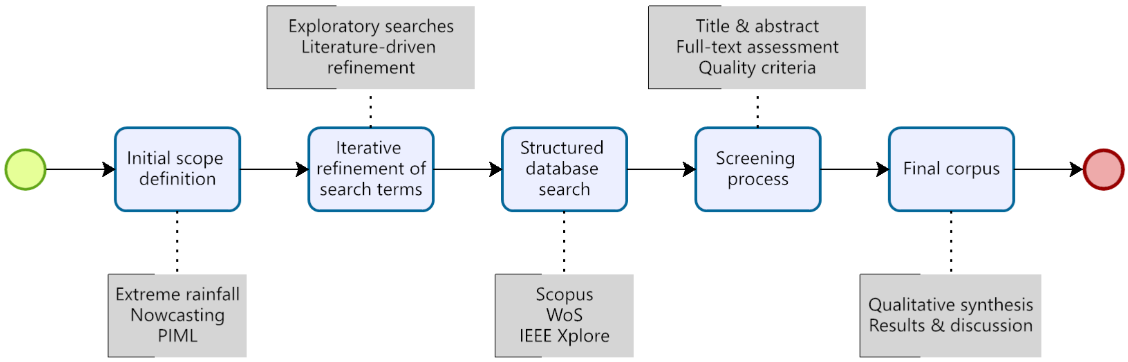

Figure 1. Overview of the Rapid Review process adopted in this study, including term refinement, structured database search, screening, and qualitative synthesis.

4. Results and Discussions

This section presents the results of the RR, starting with an overview of the search outcomes and study selection process, followed by a synthesis of the selected studies and their main characteristics.

4.1. Search Results and Study Selection

The systematic search across scientific databases retrieved an initial total of 162 records (80 from Scopus, 70 from Web of Science, and 12 from IEEE Xplore). In the first stage of identification, 62 records were removed: 57 due to duplication across databases and 5 because they were not published in English or Portuguese.

After this initial filtering, 100 unique studies were screened based on title and abstract. This stage resulted in the exclusion of 74 records that did not align with the specific scope of extreme rainfall nowcasting or lacked explicit integration of physical knowledge. Of the remaining 26 reports sought for retrieval, 3 were not retrieved, leaving 23 studies for full-text eligibility assessment.

During the final qualitative assessment, 3 additional studies were excluded: one for being outside the lead-time scope (e2) and two for not meeting the PIML integration criteria (e3). Consequently, the final corpus for data extraction and qualitative synthesis comprises 20 high-quality studies. Figure 2 illustrates this selection process through the PRISMA 2020 flow diagram [Page et al. 2021]. The final corpus forms the basis for the qualitative analysis presented in this study.

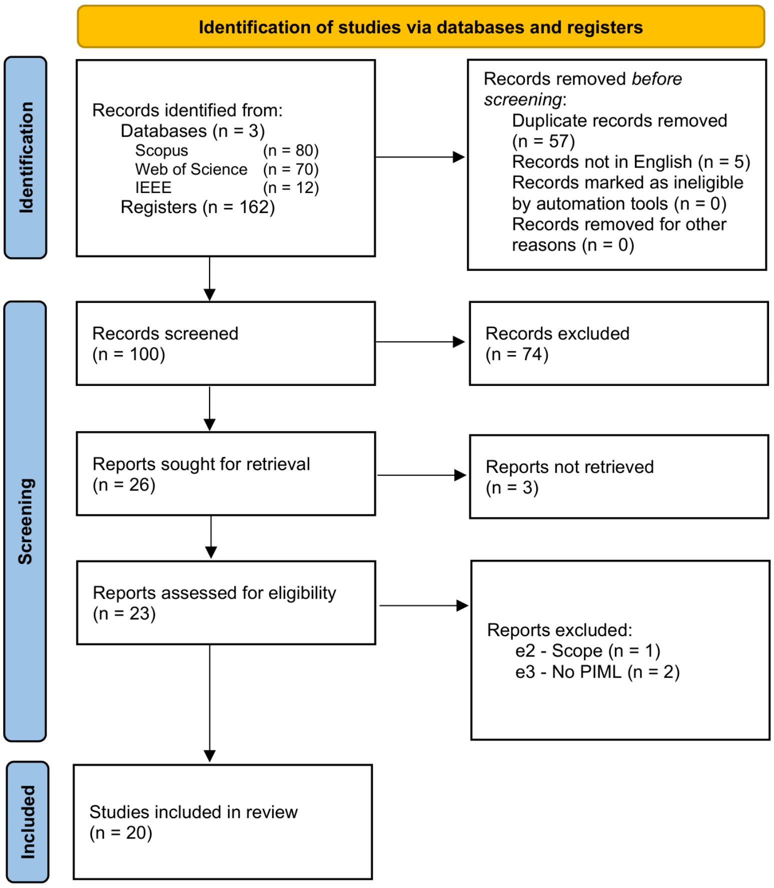

Figure 2. PRISMA 2020 flow diagram illustrating the study selection process, from identification to the final inclusion of 20 studies for qualitative synthesis.

4.2. Overview of Selected Studies

This subsection presents an overview of the 20 studies selected for qualitative analysis. These works represent the current state-of-the-art in integrating physical knowledge with machine learning, specifically focusing on the challenges of extreme rainfall nowcasting and short-term precipitation forecasting. Table 1 summarizes the final corpus, providing a consolidated reference of authors, publication years, and the primary modeling focus.

For readability purposes, study titles are presented in shortened form, while the complete titles and corresponding study identifiers are available in the online repository [de Vasconcelos 2026]. The selected studies, published between 2021 and 2026, were retrieved from leading scientific databases (including Scopus, Web of Science, and IEEE Xplore), ensuring that the sample consists of peer-reviewed research subject to rigorous technical evaluation. This selection reflects the transition from purely data-driven models to hybrid and physics-informed architectures within the meteorological domain.

This consolidated list serves as the foundation for the subsequent sections, where each study is analyzed regarding its PIML integration strategy, the specific physical laws incorporated, and the computational efficiency reported. Additional metadata and supplementary materials are available in the online repository [de Vasconcelos 2026].

Table 1. Selected studies on PIML applied to extreme rainfall and precipitation nowcasting (st01–st20)

ID	Title	First Author	Year
st01	Deep Network with Physical-Residual Fusion for Radar Extrapolation	Yang et al.	2021
st02	Scientific Knowledge in DL for Radar Nowcasting	Danpoonkij et al.	2021
st03	Deep Generative Models for Radar Nowcasting	Ravuri et al.	2021
st04	Hybrid WRF and ML for Convective Forecasting	da Silva et al.	2022
st05	Physics-Constrained Dual-Polarization Radar Nowcasting	Wang et al.	2023
st06	Lightweight Physics-Informed Transformer for Nowcasting	Li et al.	2023
st07	Extreme Precipitation Nowcasting with NowcastNet	Zhang et al.	2023
st08	Hybrid Physics-AI for Extreme Precipitation Nowcasting	Das et al.	2024
st09	Optical Flow and DL Hybrid for Radar Extrapolation	Wang et al.	2024
st10	Physics-Informed GAN for Precipitation Nowcasting	Yin et al.	2024
st11	ConvKAN for Radar Echo Extrapolation and Nowcasting	Cheng et al.	2025
st12	Lagrangian CNN for Physics-Informed Nowcasting	Pavlík et al.	2025
st13	Multi-scale Physics-Informed Transformer for Nowcasting	Zheng et al.	2025
st14	Multi-Modal Physics-Informed Nowcasting (PiMMNet)	Yu et al.	2025
st15	Motion-Dependent Physics-Informed DL Framework (ThoR)	Gia et al.	2025
st16	Multiphysical Parameter Fusion for Radar Nowcasting	Ye et al.	2026
st17	Physics-Constrained Encoder-Decoder Network (PCEED-Net)	Chi et al.	2026
st18	3D Radar Extrapolation with Physics-Constrained DL	Geng et al.	2026
st19	Physics-Informed GAN with Attention (TriPhysGAN-Attn)	Zhang et al.	2026
st20	3D Polarimetric Radar with Physics-Constrained DL	Pan et al.	2026

4.3. Analysis of PIML Approaches

To analyze the PIML strategies identified in the selected studies, this work adopts a taxonomy of physics-informed approaches based on the literature [Kashinath et al. 2021]. The considered approaches include: (a01) custom-designed loss functions or physics-based regularization, (a02) custom neural network architectures for enforcing physical constraints, (a03) symmetries and invariances, (a04) stochastic modeling, (a05) stability constraints, (a06) multiscale and spectral methods, (a07) spatiotemporal coherence, (a08) physics-based modeling frameworks, (a09) interpretability, and (a10) uncertainty quantification. Each study was classified according to these categories, enabling a structured comparison of different forms of physical knowledge integration.

In addition, we consider three levels of physics integration, ranging from explicit incorporation of physical laws to hybrid and implicit forms of inductive bias. Explicit approaches directly embed physical equations or constraints into the learning process. Hybrid approaches couple data-driven models with numerical simulations or physics-based components. Implicit approaches promote physically consistent behavior indirectly through mechanisms such as spatiotemporal coherence, probabilistic modeling, or regularization strategies.

Table 2 summarizes the analysis of the selected studies, including the machine learning models, PIML strategies, level of physics integration, and whether computational efficiency is explicitly addressed. For brevity, study titles are omitted in Table 2, since they are summarized in Table 1.

Based on the analysis summarized in Table 2 and illustrated in Figures 3 and 4, the main findings can be organized into key analytical dimensions. These dimensions highlight how physical knowledge is incorporated into machine learning models, the pre-

Table 2. Comparative analysis of PIML approaches in extreme rainfall nowcasting studies

ID	ML Model	PIML Approaches	Level	Eff.
st01	CNN + RNN	(a02), (a08)	1	No
st02	CNN (U-Net)	(a02), (a08)	1	No
st03	GAN / DGMR	(a04), (a07), (a08)	3	No
st04	RF + ML	(a06)	2	No
st05	GAN-based	(a01), (a08)	2	No
st06	Lightweight Transformer	(a01), (a02), (a08)	1	Yes
st07	Generative + Evolution	(a02), (a04), (a08)	1	No
st08	Generative Model	(a01), (a08)	2	No
st09	Swin + LSTM	(a02), (a07), (a08)	2	No
st10	GAN + Transformer	(a01), (a02), (a08)	1	No
st11	CNN (ConvKAN)	(a02), (a07)	3	Yes
st12	CNN (Double U-Net)	(a01), (a08)	1	Yes
st13	Transformer + U-Net	(a01), (a02), (a06), (a07), (a10)	1	Yes
st14	CNN + Diffusion	(a02), (a04), (a08), (a10)	1	No
st15	Attention + Motion	(a01), (a02), (a04), (a10)	1	No
st16	CNN + Attention	(a03), (a08)	3	No
st17	CNN + Encoder–Decoder	(a01), (a02)	1	No
st18	Transformer + Diffusion	(a01), (a02), (a04), (a08)	1	No
st19	GAN + Attention	(a01), (a02), (a04), (a08), (a10)	1	No
st20	Encoder-Decoder	(a02), (a04)	1	No

dominant modeling strategies, and the main gaps identified in the literature.

Physics integration levels. The results indicate a strong predominance of Level 1 approaches, suggesting that recent works tend to incorporate physical constraints explicitly into machine learning models. Hybrid approaches (Level 2) are less frequent, while implicit strategies (Level 3) appear only in a minority of studies.

PIML strategies. Custom neural architectures (a02) and physics-based modeling frameworks (a08) are the most frequently adopted approaches, highlighting a clear trend toward embedding physical knowledge directly into model design. In contrast, strategies based on symmetries and uncertainty quantification remain less explored, while interpretability approaches were not identified in the selected studies.

Computational efficiency. Despite recent advances, only 20% of the studies explicitly address computational efficiency, while 80% do not consider efficiency-related aspects. This reveals a critical gap in the development of sustainable and deployable nowcasting systems.

Modeling paradigms. The analyzed studies predominantly rely on deep learning architectures, including convolutional, transformer-based, and generative models, often combined with motion estimation or multimodal inputs. The diversity of model architectures indicates that PIML strategies are being explored across different deep learning paradigms.

Research gaps. Several recurring challenges were identified. Many studies strug-

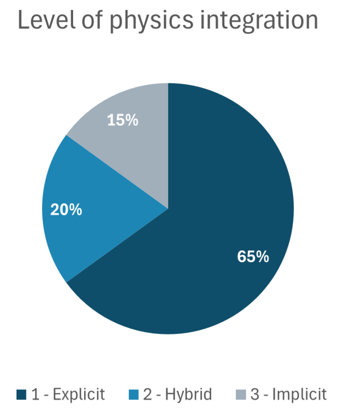

Figure 3. Distribution of physics integration levels across the selected studies

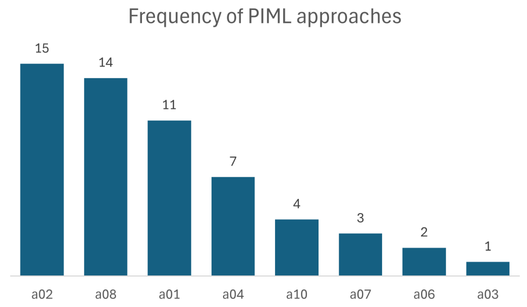

Figure 4. Frequency of PIML approaches identified in the selected studies

gle to capture complex spatiotemporal dependencies without increasing model complexity. Additionally, the absence of explicit interpretability approaches reinforces the black-box nature of most deep learning models. From a physical perspective, incomplete incorporation of physical knowledge can lead to inconsistencies, while generalization across regions and datasets continues to be a challenge. To further support the analysis, the selected studies can be grouped according to their level of physics integration and modeling strategies.

Studies adopting *explicit physics integration* (Level 1) represent the majority of the analyzed works. These approaches incorporate physical constraints directly into the learning process, either through loss functions or model architectures. Representative examples include st06, st07, st10, st13, st15, st17, st18, and st19, which cover strategies ranging from transformer-based formulations and motion-aware architectures to diffusion and generative models with embedded physical constraints.

Some studies explicitly incorporate physical constraints through loss functions or motion-aware formulations (e.g., st06, st15, st17, st18), while others embed physical knowledge through architectural design or hybrid generative frameworks (e.g., st07, st10, st13, st19). This diversity highlights the multiple ways physical consistency can be incorporated into deep learning models for nowcasting.

A second group corresponds to *hybrid approaches* (Level 2), where machine learning models are combined with external physical components or partially integrated physical constraints. Representative studies include st04, st05, st08, and st09.

Some works rely on coupling ML with established physical models or numerical weather prediction systems (e.g., st04), leveraging large-scale physical simulations to support data-driven predictions. Other approaches incorporate intermediate physical components, such as motion estimation through optical flow (st09), to guide the learning process. Additionally, certain models introduce localized physical constraints within deep learning architectures without fully embedding governing equations (e.g., st05 and st08). Overall, these approaches benefit from combining data-driven learning with physical insights, but the integration is typically less tightly coupled than in Level 1 methods.

A third group includes studies with *implicit physics integration* (Level 3), where physical consistency is encouraged indirectly rather than enforced through explicit constraints or equations. Representative examples include st03, st11, and st16. These approaches typically rely on learned representations, architectural design choices, or physically meaningful input variables to capture underlying physical behavior. For instance, some models improve the representation of spatiotemporal dynamics through advanced architectures (st11), while others leverage multimodal inputs derived from physical measurements (st16). Generative models such as st03 learn precipitation patterns directly from data without explicitly encoding physical laws.

Although these approaches can achieve strong predictive performance, they do not guarantee physical consistency, as the incorporation of physical knowledge remains indirect and data-driven. Across all groups, a common limitation is the lack of explicit consideration of computational efficiency from a resource-aware perspective. Although a small number of studies (e.g., st06, st11, st12, and st13) introduce architectural optimizations or lightweight designs, these efforts primarily target structural efficiency or inference speed rather than providing a comprehensive evaluation of computational cost.

In particular, none of the analyzed works report metrics related to energy consumption, carbon emissions, or hardware usage, such as those estimated by tools like CodeCarbon. As a result, aspects such as training cost, GPU utilization, and environmental impact remain largely unaddressed. This gap is especially relevant in the context of deep learning-based nowcasting, where increasingly complex models can lead to significant computational and environmental costs. The analysis suggests that efficiency considerations remain limited across all levels of physical integration, indicating that increased physical consistency does not necessarily translate into resource-aware design.

Overall, these findings indicate that current research is primarily driven by predictive performance and the incorporation of physical knowledge. However, this evolution is not accompanied by a proportional focus on sustainable AI practices. This highlights the need for future research to jointly consider physical consistency, predictive performance, and resource-aware efficiency, particularly in real-time and operational early warning systems.

5. Conclusion

This paper presented a Rapid Review of PIML approaches applied to extreme rainfall nowcasting. The study synthesized recent literature, identifying key models, strategies for integrating physical knowledge, and common challenges in this domain.

The findings indicate that, although PIML has gained increasing attention, the literature remains fragmented, with heterogeneous terminology (e.g., physics-informed, physics-guided, physics-constrained, and hybrid approaches) and varying levels of physical integration. Most studies primarily focus on improving predictive performance, while aspects such as computational efficiency and sustainability remain largely underexplored. In particular, no study explicitly evaluates resource-aware metrics, such as energy consumption or environmental impact, revealing an important gap from a Green AI perspective. Additionally, only a limited number of works explicitly address extreme rainfall nowcasting, highlighting a gap between general precipitation forecasting and high-impact urban applications.

This work contributes by providing a structured taxonomy of PIML approaches and organizing different forms of physical knowledge integration into a unified framework. This organization facilitates a more consistent comparison of methods across the field. To the best of our knowledge, this is one of the first studies to explicitly analyze PIML for extreme rainfall nowcasting from a resource-aware perspective.

Future work includes a deeper quantitative analysis of the selected studies is planned, including a comparative evaluation of models, datasets, and performance metrics. Furthermore, the development of standardized evaluation frameworks that jointly consider predictive performance, physical consistency, and computational efficiency represents an important research direction toward more reliable, sustainable, and deployable nowcasting systems.

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