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A LITERATURE SURVEY OF: QUANTUM AND CLASSICAL MACHINE LEARNING APPROACHES FOR REAL-TIME CLIMATE-INDUCED FLOOD RISK AND DISASTER MANAGEMENT USING OPERATIONAL HYDROLOGICAL AND GEOSPATIAL DATA

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Abstract:

This survey synthesizes recent advances in applying advanced machine learning and quantum machine learning (QML) techniques to climate-related risk and disaster management, with a particular focus on floods. It first reviews how QML is being explored for broad climate and sustainability applications—including DE carbonization, forecasting, environmental monitoring, and hazard prediction—highlighting hybrid quantum–classical architectures and their reported advantages over purely classical models, as well as the hardware and algorithmic constraints that currently limit large-scale deployment. It then summarizes case studies where classical and quantum-enhanced models are evaluated for daily flood prediction on Germany's Wupper River and for three decades of flood prediction in Sacramento, California, using algorithms such as SVM, Random Forest, ANN, and LSTM to capture nonlinear hydrological dynamics and the influence of large-scale climate drivers on local flood patterns. Beyond individual river basins, the survey incorporates a broader review of how machine learning and deep learning are applied across the disaster management cycle—from mitigation and preparedness to response and recovery—for tasks such as hazard prediction, vulnerability assessment, early warning, mapping, and post-disaster damage analysis, leveraging data from satellites, UAVs, GIS, sensors, and social media. Finally, it includes studies that use Random Forest, SVM, and ANN to generate flood-susceptibility maps in data-scarce regions (e.g., Jordanian watersheds) based on simulated flood points and multiple terrain and hydrologic predictors, assessing model robustness across contrasting climatic regimes and identifying key controlling factors such as distance to stream, elevation, and drainage characteristics. Together, these works demonstrate the growing role of classical and quantum machine learning in climate adaptation and flood-risk reduction, while underscoring the need for better data, more robust models, and scalable quantum hardware to fully realize their potential.

Key words: Quantum machine learning, SVM, ANN, LSTM, flood Susceptibility, hydrological predictors, hazard prediction and flood risk reduction.

Introduction:

Climate change, disaster resilience, and sustainable development pose increasingly complex and data-intensive challenges for society, requiring advances in predictive analytics, risk assessment, and early warning systems. In these domains, conventional machine learning has transformed data analysis but is now encountering limitations as the scale, heterogeneity, and non-linearity of climate and disaster data escalate. Quantum machine learning (QML) emerges as a frontier approach, fusing quantum computation's unique properties—such as superposition and entanglement—with powerful learning models to address high-dimensional optimization, time-series forecasting, and pattern recognition tasks in sectors like energy, environmental monitoring, transportation, and agriculture.
This technology shows promise for extending flood prediction, especially in settings plagued by nonlinear hydrological behaviors and sparse observational data, such as arid or semi-arid regions and rapidly urbanizing floodplains. At the same time, the proliferation of multi-source big data—from satellites, UAVs, GIS, sensors, and social media—demands robust AI
Frameworks, motivating reviews that systematically map machine learning and QML methods to key disaster management tasks, including hazard and vulnerability assessment, mitigation and preparedness, real-time response, and damage [7].
Mapping. Machine learning offers a practical alternative to traditional physics-based models, particularly where data availability or speed is limited, and QML provides additional potential for expressivity and computational gains.
Together, these trends are catalyzing the integration of advanced computational models, both classical and quantum, into operational workflows for climate adaptation and disaster risk management, with the ultimate goal of building smarter, more resilient, and sustainable communities.

A literature survey 1: "Quantum Machine Learning in Climate Change and Sustainability: A Short Review"

Overview of the topic:
Climate change and global sustainability create complex, data-intensive problems in areas such as energy systems, climate forecasting, and environmental monitoring [1]. Quantum machine learning (QML) has been proposed as a way to combine quantum computing with machine learning to address some of the computational and modeling limitations of classical methods in these domains. The reviewed paper surveys recent work where QML techniques are applied specifically to climate change mitigation, adaptation, and broader sustainability use cases.

Quantum machine learning foundations:
The paper introduces[1] basic quantum computing concepts, explaining that quantum information is encoded in qubits that can exist in superposition and become entangled, unlike classical bits that are restricted to definite 0 or 1 values. These quantum properties, together with quantum gates and circuits, allow certain computations to be performed more efficiently than on classical hardware, which motivates their use in data-driven climate applications. QML is presented as a family of hybrid quantum–classical approaches, including quantum neural networks and other parametric quantum circuits that can be trained similarly to classical models but operate partly in a quantum Hilbert space.

QML for DE carbonization and energy systems:
A substantial part of the surveyed work focuses on DE carbonization, particularly quantum-enhanced control and optimization in power and energy systems [1]. Reported examples include multi-agent quantum deep reinforcement learning for distributed frequency control in islanded micro grids, quantum reinforcement learning for energy-efficient HVAC control and electric-vehicle energy management, and quantum neural-network controllers for photovoltaic maximum power point tracking. These studies typically find that QML-based or hybrid methods can reduce parameter counts or improve control accuracy relative to classical baselines, although training and execution may be slower because current implementations rely on quantum simulators and hybrid loops.

Applications in transportation, agriculture, and forecasting:

In transportation, hybrid schemes that combine meta-heuristic optimizers with quantum neural networks have been applied to joint placement of electric-vehicle charging stations and capacitors in distribution systems, aiming to improve voltage profiles and lower active power losses [1]. Quantum reinforcement learning combined with block chain has been used for energy trading in e-mobility micro grids, where QML-based policies are reported to converge faster and yield better utilities than classical trading mechanisms. For agriculture, comparative experiments on wheat disease prediction show that, [6]

When quantum models are run on classical simulators, a classical convolutional neural network can still outperform quantum neural and quantum convolutional neural networks, underlining the gap between theoretical quantum advantages and present-day hardware constraints.

For time-series forecasting, the survey covers QML approaches for weather prediction, solar irradiation, wind speed, load, and carbon price forecasting. Quantum support vector machines and vibrational quantum-circuit models are explored for radiation and weather time series, while hybrid quantum–LSTM and quantum LSTM (QLSTM) architectures are developed for short-term solar and wind forecasting, [6]usually achieving higher accuracy than standard models such as CNN, RNN, GRU, or classical LSTM but with longer training times. Similar hybrid architectures are adapted for carbon price forecasting, where quantum-enhanced models can reach comparable or slightly better performance than classical recurrent networks.

QML for climate monitoring and hazard prediction:

The paper [1] reports several studies applying QML to remote sensing and earth observation, especially classification of hyper spectral and multispectral satellite imagery for land-cover and vegetation mapping. Quantum classifiers, quantum convolutional neural networks, and models using projected quantum kernels often show that incorporating quantum features or entanglement can improve accuracy or achieve competitive results with fewer parameters compared to some classical baselines, although some quantum classifiers still lag behind state-of-the-art classical remote-sensing methods. In climate-related hazard prediction, QML has been used for earthquake prediction with quantum support vector machines and for classifying potentially hazardous asteroids with variation AL, quantum circuits, where the reported experiments achieve high accuracy and F1-scores, suggesting that QML may be well suited to certain complex, imbalanced classification tasks.

Challenges and future research directions:

According to the survey [1], major theoretical and practical challenges limit current QML deployment in climate applications. On the theory side, there is tension between the linear evolution of quantum states and the non-linear activations required for expressive neural networks, complicating QNN design. On the hardware and implementation side, limited numbers of qubits, DE coherence, noise, circuit depth and width constraints, measurement sampling overhead, and costly classical-to-quantum data encoding all reduce scalability and often make hybrid quantum–classical pipelines slower than purely classical solutions today.[7] Many studies also assume idealized quantum simulators and effectively unlimited measurement shots, which may not reflect realistic quantum hardware.

The paper concludes that QML is still in an early, exploratory stage for climate change and sustainability, with current work concentrated on quantum-enhanced optimization, time-series forecasting, and image classification. It identifies future opportunities in large-scale climate systems modeling, quantum-level material simulation for climate-relevant materials, advanced climate data analytics, and improved prediction of extreme events, contingent on progress in quantum hardware, error correction, and scalable QML architectures.

A literature survey 2:"Flood Prediction Using Classical and Quantum Machine Learning Models"

Overview and motivation:

Flooding is identified as a major natural disaster whose prediction remains challenging due to complex, non-linear environmental patterns and growing data volumes [2]. The paper aims to investigate whether quantum machine learning (QML) can improve daily flood forecasting along Germany's Wupper River in 2023 compared with Purely classical machine learning models. By exploring hybrid classical–quantum Approaches, the study positions QML as a potential tool for climate-change adaptation and real-time flood management.

Methods and models:
The authors build a hybrid framework that combines classical machine learning models[2]—Support Vector Machines (SVM), K-Nearest Neighbors (KNN), linear regression, and autoregressive (AR) time-series models—with QML techniques including Adaboost with quantum-enhanced weak learners, quantum variational circuits, QBoost, and quantum SVM variants (QSV C_ML). Classical models are used to classify and regress flood occurrence and magnitude based on hydrological inputs such as rainfall and river discharge,[8] while quantum-enhanced models exploit superposition and entanglement to process patterns in higher-dimensional feature spaces more efficiently. The study compares classical and quantum models using metrics such as prediction accuracy, training time, and scalability to assess suitability for operational flood forecasting.

Key findings:
Results reported in the paper indicate [2] that QML-based or quantum-enhanced models achieve higher or at least competitive prediction accuracy relative to their classical counterparts on the Wupper River dataset. In particular, ensemble and boosting-style QML approaches (e.g., quantum-enhanced Adaboost, QBoost) benefit from quantum parallelism to strengthen weak classifiers and improve classification of flood versus non-flood days. The authors note that, within the experimental setup, quantum models offer competitive training times and favorable scalability characteristics, suggesting that they could become viable for near–real-time flood prediction as quantum hardware matures.[9] Overall, the study concludes that integrating QML into flood-prediction pipelines is a promising step toward more resilient flood-risk management under climate change.

Limitations and future directions:
The paper acknowledges several limitations [2] that currently constrain practical deployment of quantum-enhanced flood models. First, hardware restrictions—limited qubit counts, short coherence times, and high error rates—limit the scalability and reliability of QML implementations, forcing the authors to rely on simulators rather than large-scale quantum devices. Second, data availability and quality issues in some regions restrict model training and validation; the authors emphasize the need for richer, standardized historical flood datasets to improve robustness and generalization. They suggest future work on integrating multi-source data (e.g., satellite imagery, sensor networks, and social media) and combining hydrological process models with quantum-enhanced learning to build more powerful, real-time decision-support systems for disaster management agencies.

A literature survey 3: "Analyzing Climate Dynamics and Developing Machine Learning Models for Flood Prediction in Sacramento, California"

Overview and motivation:
The paper addresses the growing flood risk in Sacramento, California, driven by climate-change-induced shifts in precipitation, temperature, and soil moisture patterns over recent decades [3]. Its main objectives are to analyze long-term climate and rainfall dynamics in the Sacramento region and to develop data-driven machine learning models that can predict flood occurrences using historical
Hydro-climatic variables. By focusing on a vulnerable urban area with a history of severe flooding, the study positions machine learning as a tool for early warning and climate-risk management[10].

Methods and models:
The authors examine four supervised classification models[3]—Support Vector Machine (SVM), Random Forest (RF), Artificial Neural Network (ANN), and Long Short-Term Memory (LSTM)—for their ability to predict flood events from daily time-series of precipitation, temperature, and soil moisture. Historical data cover a 32-year period with 11,680 daily records, which are standardized (e.g., using a scalar) and reshaped as needed for sequential modeling in LSTM.[11] The ANN architecture uses two hidden layers with 64 neurons each, RELU activations, dropout for regularization, and is trained with the Adam optimizer and binary cross-entropy loss, while the LSTM architecture is tuned with Keras Tuner to select the number of LSTM units, dense units, learning rate, and dropout, and then trained over multiple epochs with validation splits.

Performance is evaluated using hydrological efficiency and error metrics (RMSE, NSE, PBIAS, R2*R*2, NRMSE) along with classification measures (precision, recall, F1-score, AUC) derived from confusion matrices and ROC curves to provide a comprehensive assessment of each model's predictive capability.

Key findings:
The results show that the LSTM model achieves the highest flood prediction accuracy (about 89.99%) among the four models, which the authors attribute to its capacity to capture complex temporal dependencies in the long rainfall and climate time series [3]. ANN, RF, and SVM attain accuracies of approximately 85%, 83.75%, and 81.25%, respectively, indicating that deep learning models generally outperform traditional machine learning methods for this sequential prediction task. Analysis of historical data reveals strong correlations between increased precipitation extremes, El Niño/La Niña cycles, and observed flood events, with notable rainfall peaks around 1998 and 2007 that suggest significant influence from large-scale atmospheric drivers on local flood risk. The authors conclude that, although LSTM performs best among the tested models, there is still room for improvement, particularly for extreme flood scenarios.

Limitations and future directions:
The study notes that model performance is constrained by the available data, which are limited to a single region and may not fully capture rare or extreme flood events, reducing generalizability and robustness in the most critical cases.[3] While LSTM demonstrates high accuracy, the authors recognize that its adaptability to unprecedented extremes and changing climate regimes is not fully guaranteed and that over fitting must be carefully controlled with regularization and validation strategies. Future research directions proposed include integrating additional environmental data sources (e.g., more detailed hydrological measurements, remote-sensing products), exploring hybrid and ensemble modeling approaches that combine different algorithms, and extending the methodology to other flood-prone regions to test transferability and scalability.

A literature survey 4:"Machine Learning in Disaster Management: Recent Developments in Methods and Applications"

Scope and motivation:
The paper reviews how machine learning (ML) and deep learning (DL) have been applied across the full disaster management cycle—mitigation, [4] preparedness, response, and recovery—for both natural and man-made disasters since about 2017.[12] It is motivated by the increasing frequency and severity of climate-related disasters (storms, floods, wildfires, landslides) and the availability of big, heterogeneous data (satellites, UAVs, sensors, social media) that require advanced AI methods for timely, accurate decision support.

Methods and taxonomy:
The authors conduct a structured review of ML/DL methods used in disaster management, grouping them by both algorithm type and application task [4]. Classical ML techniques covered include SVM, Naïve Bayes, decision trees, random forest, logistic regression, and k-nearest neighbors, while DL covers CNNs, MLPs, RNNs, LSTMs, transformers, and GANs. The paper organizes applications into key functional areas such as hazard and disaster prediction, risk and vulnerability assessment, early warning systems, disaster detection and monitoring, damage assessment, post-disaster response, and case studies,[13] mapping which ML/DL families are most commonly used in each area.

Main findings:
The review shows a strong trend toward using DL, especially CNNs and LSTMs, for tasks involving imagery, spatiotemporal data, and sequence prediction (e.g., event detection from satellite/UAV images, rainfall–runoff or flood forecasting [4], wildfire spread modeling). Classical ML algorithms remain prevalent for structured tabular data in risk and vulnerability assessment, damage classification, and resource-allocation problems due to their interpretability and lower computational cost. The authors highlight that AI techniques enable integration of big, multi-source data (remote sensing, social media, GIS, sensor networks) to support early warning, situational awareness, and rapid damage mapping in near real time. They also note a growing number of practical

decision-support tools and prototypes that translate ML/DL outputs into actionable information for emergency managers.

Limitations and research gaps:
The paper points out that many existing studies are developed on limited case-study regions or specific hazard types, which raises concerns about generalization to other geographic or socio-economic contexts. Data quality, biases, and lack of standardized datasets are recurring issues, especially when using social media and crowd sourced data for disaster detection and situational awareness. The authors stress that relatively few works address interpretability, uncertainty quantification, or robust performance under data scarcity and changing hazard patterns, which are critical for operational disaster management. [4]They call for more work on integrating ML/DL with domain models, ensuring interoperability with existing emergency systems, and involving local communities to enhance resilience.

A Literature survey 5:" Robustness of machine learning algorithms to generate flood susceptibility maps for watersheds in Jordan"

Scope and motivation:
The paper focuses [5] on generating flood susceptibility maps for two Jordanian watersheds (Al-Buaida and Zarqa Ma'in), representing desert and mountainous climatic regimes, using machine learning algorithms instead of traditional hydrologic–hydraulic models. It is motivated by increasing flash-flood frequency in arid and semi-arid regions, the need to identify areas prone to flooding for mitigation and planning, and limitations of existing methods such as subjective multi-criteria decision analysis and computationally expensive physical models.

Methods and data:
Three machine learning algorithms [5]—Random Forest (RF), Support Vector Machine (SVM), and Artificial Neural Network (ANN)—are evaluated for flood susceptibility mapping. Because historical flood location data are scarce, the authors first use a physical model to simulate flood occurrence under a 100-year rainfall scenario and then randomly select 10,000 simulated flood/non-flood points for training [14]
and testing the ML models. Thirteen flood-influencing factors (e.g., distance to stream, elevation, stream density, topographic wetness index) are used as predictors, and information gain ratio (IGR) is applied
to quantify each factor's importance in each watershed.

Main findings:
The analysis shows[5] that a small subset of variables dominates flood susceptibility: in Zarqa Ma'in, distance to stream, elevation, and topographic wetness index contribute about 50% of the IGR, while in Al-Buaida, distance to stream, stream density, and elevation contribute about 44%. Among the tested algorithms,[15] Random Forest consistently outperforms SVM and ANN in both watersheds and is therefore selected to produce the final susceptibility maps. The resulting RF-based maps, classified into five susceptibility classes, indicate that about 11% of the Al-Buaida watershed and 5.2% of the Zarqa Ma'in watershed fall into high to very-high flood-susceptibility zones, highlighting priority areas for mitigation and land-use planning. The authors conclude that ML algorithms can efficiently generate reliable flood susceptibility maps and offer a practical alternative to purely physical modeling approaches.

Limitations and implications:
The study's approach depends [5] on simulated flood locations derived from a single 100-year rainfall scenario, so the realism of susceptibility patterns is tied to the assumptions and parameterization of the underlying physical model. Limited observational flood data in Jordan also constrain model validation and may introduce uncertainty about performance under real, multi-event conditions. Nonetheless, the work demonstrates that ML-based susceptibility mapping is feasible and robust across contrasting climatic regimes and can support adaptation strategies in data-scarce arid and semi-arid regions.

Table1:Literature survey table

Title	***Machine Learning in Disaster Management: Recent Developments in Methods and Applications.* (2022)**	***Quantum Machine Learning in Climate Change and Sustainability: A Short Review. (2023)***	***Flood Prediction Using Classical and Quantum Machine Learning Models. (2023)***	***Analyzing Climate Dynamics and Developing Machine Learning Models for Flood Prediction in Sacramento, California* (2024)**	**Robustness of machine learning algorithms to generate flood susceptibility maps for watersheds in Jordan (2024)**
Problem stateme nt	The paper addresses the lack of a focused, up-to-date overview of how machine learning (ML) and deep learning (DL) methods are being used across all phases of disaster management (mitigation, preparedness, response, recovery) for natural and man-made disasters, given the rapid growth of AI techniques and big disaster-related data.	The paper investigates how quantum machine learning (QML) can be used to address climate-change and sustainability problems more efficiently than classical machine learning, focusing on domains such as DE carbonization, climate and energy forecasting, climate monitoring, and hazard prediction, and aims to survey existing QML applications, their benefits, and open challenges in these areas.	The paper addresses the problem of accurately predicting floods along Germany's Wupper River under changing climate conditions, asking whether quantum machine learning (QML) can provide better or more scalable flood prediction than established classical machine learning models.	The paper addresses the problem of increasing flood risk in Sacramento, California, under changing climate conditions and asks how well different machine learning models (SVM, Random Forest, ANN, LSTM) can predict flood occurrences using multi-decade daily climate and rainfall data.	The paper addresses how to reliably generate flood susceptibility maps for arid and semi-arid watersheds in Jordan (Al-Buaida and Zarqa Ma'in) using machine learning, given scarce historical flood data and limitations of traditional hydrologic–hydraulic and subjective multi-criteria methods.
methods	The authors conduct a structured literature review of recent studies (mainly after 2017) that apply ML and DL to disaster management, classifying them by algorithm family (e.g., SVM, Naïve Bayes, decision	The authors perform a narrative literature survey of studies that apply QML techniques (e.g., quantum neural networks, quantum reinforcement learning, quantum support vector machines, variation quantum circuits, quantum LSTM) to climate-relevant tasks including	The authors develop and compare a set of classical models (e.g., Support Vector Machines, logistic/linear regression, KNN, LSTM/AR-type time-series models) with quantum and quantum-enhanced models such as Quantum Support Vector Machines,	The authors analyze 32 years of daily hydro-climatic data (11,680 records) for Sacramento, including rainfall, temperature, and soil moisture, then build and compare four supervised	Three machine learning algorithms—Random Forest (RF), Support Vector Machine (SVM), and Artificial Neural Network (ANN)—are trained and tested on 10,000 randomly sampled points of simulated

	trees, random forest, KNN, logistic regression, CNN, MLP, RNN, LSTM, transformers, GANs) and by application area such as hazard prediction, vulnerability and risk assessment, early warning systems, disaster detection and mapping, damage assessment, rescue/relief, and resource allocation	energy-system optimization, transportation and e-mobility, agriculture, time-series forecasting, satellite/remote-sensing image classification, and natural-hazard prediction, grouping the works by application category and then synthesizing trends, challenges, and future directions.	QBoost/QBoost+, and other variation-circuit-based learners, using hydrological and meteorological data (e.g., rainfall, river levels) from the Wupper region in 2023 to model flood occurrence and severity.	models: SVM, Random Forest, an ANN with two 64-neuron hidden layers (ReLU, dropout, Adam, binary cross-entropy), and an LSTM tuned via Keras Tuner with standardized and reshaped time-series inputs; model performance is evaluated using RMSE, NSE, PBIAS, R2*R*2, NRMSE, plus precision, recall, F1-score, AUC, confusion matrices, and ROC curves.	flood/non-flood locations derived from a physical model under a 100-year rainfall event for each watershed . Thirteen flood-conditioning factors (e.g., distance to stream, elevation, stream density, slope, topographic wetness index) are used as predictors, and information gain ratio (IGR) is applied to assess the relative importance of each factor in each basin before using the best-performing ML model to produce final susceptibility maps with five classes from very low to very high.
Key results	The review finds a strong trend toward using DL—especially CNNs for image-based tasks and LSTMs/RNNs for time-series and sequence modeling—while classical ML remains widely used for structured tabular data in risk assessment, vulnerability	1) In DE carbonization and energy systems, QML and hybrid quantum–classical controllers often achieve higher control accuracy, better frequency regulation, or fewer parameters than classical methods in simulation studies. 2) For time-series forecasting of weather, solar irradiance, wind speed, load, and	The study finds that quantum and quantum-enhanced models can achieve prediction accuracy that is competitive with, and in some cases better than, the best classical models for the Wupper River flood dataset, especially when using boosting-style quantum ensembles (e.g., QBoost) and	The LSTM model achieves the highest flood-prediction accuracy (around 89.99%), outperforming ANN (~85%), Random Forest (~83.75%), and SVM (~81.25%), showing that deep sequential models best capture temporal	IGR analysis shows that a few key factors dominate flood susceptibility: in Zarqa Ma'in, distance to stream, elevation, and topographic wetness index together contribute about 50% of the total IGR, while in Al-Buaida, distance to stream, stream

	analysis, and damage classification. It shows that AI methods effectively exploit big, multi-source data (satellite imagery, UAVs, GIS, social media, sensor networks) to support early warning, situational awareness, and rapid post-disaster mapping, and documents an increasing number of decision-support tools that translate ML/DL outputs into actionable information for emergency managers.	carbon prices, hybrid VQC/QLSTM models usually match or outperform classical baselines (CNN, RNN, GRU, LSTM) on accuracy metrics, albeit with longer training times. 3) In climate monitoring and hazards, QML-based satellite-image classifiers and asteroid/earthquake prediction models can provide high classification accuracy or competitive performance with reduced model size compared to some classical approaches, though results are mixed across tasks.	quantum SVM variants; the authors highlight that the hybrid and QML approaches demonstrate promising scalability characteristics for future real-time flood forecasting applications.	dependencies in the Sacramento climate and rainfall series. Long-ter m analysis reveals strong links between extreme precipitation events, large-scale climate drivers (e.g., El Niño/La Niña), and observed flood incidents, with pronounced rainfall peaks (such as around 1998 and 2007) aligning with increased flood risk.	density, and elevation account for roughly 44% . Among the three algorithms, Random Forest outperforms SVM and ANN in both watersheds and is selected as the final model, yielding susceptibility maps where approximately 11% of Al-Buaida and 5.2% of Zarqa Ma'in fall into high to very-high flood-susceptibil ity classes, providing clear spatial targets for mitigation and planning.
limitatio n	Many studies are confined to specific regions, hazards, or datasets, limiting the generalizability of models to other contexts or future climate conditions. The review highlights persistent issues with data quality, bias, and lack of standardized benchmark datasets, as well as limited attention to interpretability, uncertainty quantification,	QML applications are constrained by current quantum hardware (few qubits, noise, DE coherence, circuit-depth limits) so most experiments use classical quantum simulators rather than real devices. Hybrid pipelines incur overhead from quantum–classical communication, costly classical-to-quantu m data encoding, and the need for many measurement samples, which often makes them	The work is constrained by current quantum hardware limitations (limited qubits, coherence times, and relatively high error rates), so experiments rely on quantum simulators rather than large, fault-tolerant devices, which restricts model size and realism. In addition, limited availability and quality of historical flood data in some regions hamper model training and	The dataset is limited to one region and time period, which may not fully represent rare or unprecedented extreme floods and restricts model generalizability to other basins or future climate regimes. Althou gh LSTM performs best, its ability to handle truly novel extremes and evolving climate	The training and validation rely on simulated flood locations from a single 100-year rainfall scenario, so model performance and mapped patterns are dependent on the assumptions and parameterization of the underlying physical model rather than on long observational records. Limited real flood observations in

	operational integration with existing emergency systems, and robustness when data are scarce or hazard patterns shift over time.	slower than purely classical models despite accuracy gains. Many studies assume idealized conditions and small problems, and in some cases (e.g., wheat disease prediction) strong classical CNNs still outperform quantum and quantum-convolutional models, indicating that QML advantages are not yet consistent in practice.	validation, and the authors note that broader, more standardized datasets and advances in quantum hardware are needed before QML can be routinely used in operational flood-forecasting systems.	dynamics remains uncertain, and the authors note the need for more diverse data sources, careful regularization to avoid overfitting, and further testing before operational deployment.	Jordan restrict independent validation across multiple events and may reduce confidence in transferability to other return periods or changing climate conditions, even though the study indicates that ML models are robust across the two contrasting climatic regimes examined.
Relevance to my work	This paper offers a broad map of which ML/DL techniques are used for different disaster-management tasks and data types, helping you justify your model choices (e.g., using LSTM/CNN for flood prediction, or combining classical ML with quantum approaches) and position your work within the wider AI-for-disasters literature. You can use its identified gaps—such as generalization to new regions, integration of multiple data sources, interpretability, and operational deployment—as motivation and	This paper provides up-to-date motivation that QML is considered a promising approach for climate and sustainability tasks and can be cited to justify exploring QML or comparing it against classical ML in your project. Its application categories (energy systems, forecasting, monitoring, hazards, agriculture) help you position your topic within the broader QML-for-climate landscape, and its discussion of limitations (simulator-based experiments, hardware constraints, mixed performance vs. CNNs) can be turned into clear research gaps that	This paper is a direct precedent for using both classical ML and QML in a climate-risk application and can be cited to justify applying or comparing quantum methods in your own project (e.g., for flood, rainfall, river-flow, or other climate-related prediction tasks) . Its discussion of benefits (competitive accuracy, potential scalability) and constraints (hardware limits, data quality) provides ready-made motivation and gap statements you can use to position your work, for example by targeting richer datasets, different regions, alternative	This paper provides a complete workflow—from long-term climate analysis to comparative ML modeling—for flood prediction, which you can follow or adapt if your project also involves rainfall–runoff or flood prediction using ML or QML. You can cite it to justify using deep learning (especially LSTM) for flood or climate-related prediction, and to motivate extensions such as applying more advanced architectures (e.g., hybrid	This paper provides a clear example of using ML (RF, SVM, ANN) for flood susceptibility mapping in data-scarce regions, which you can cite to justify applying machine learning—and, in your case, extending to quantum or hybrid models—for flood prediction or susceptibility assessment. Its workflow (physical model → simulated flood points → ML with multiple predictors' → variable importance → final susceptibility map) and

	research gaps that your project on flood prediction with classical and quantum ML aims to address.	your work aims to address, such as testing QML on more realistic datasets, designing shallower circuits, or performing fair comparisons with strong classical baselines.	quantum architectures, or more realistic real-time deployment scenarios.	quantum models), including additional input variables, or testing in a different region or under future climate scenarios.	findings on key controlling factors and RF's robustness can guide your feature selection, model comparison strategy, and discussion of how your work improves on or differs from existing ML-based flood studies.

Conclusion:

Overall, the surveys show that advanced machine learning and quantum machine learning are becoming key tools for climate-related risk and disaster management, but they are at different stages of maturity. QML is still largely exploratory yet already demonstrates promise in optimization, forecasting, and remote-sensing applications for climate science, with quantum ensembles and quantum SVM variants sometimes matching or surpassing strong classical models in flood-prediction case studies such as the Wupper River. Classical deep learning, particularly LSTMs and CNNs, currently dominates practical deployments for image- and sequence-based tasks like flood prediction and damage mapping, as illustrated by the superior performance of LSTM in Sacramento flood forecasting and the broad use of DL across the disaster-management cycle. Across studies, Random Forest and a small set of geophysical variables—especially distance to stream, elevation, and flow-related indices—consistently emerge as robust components for flood-susceptibility mapping in data-scarce watersheds, supporting their use for prioritizing high-risk zones. At the same time, all lines of work highlight important limitations: dependence on simulator-based quantum experiments, constrained and region-specific datasets, limited coverage of extreme events, and gaps in generalization, interpretability, and operational integration. Future progress will require better and more diverse data, more robust and explainable models, integration with physical hydrological and climate process knowledge, and advances in scalable quantum hardware and algorithms so that both classical and quantum approaches can be reliably deployed in real-world, climate-resilient decision-support systems.

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