

2-3 マルチパラメータ・フェーズドアレイ気象レーダー (MP-PAWR) を活用したAI降水ナウキャスト

2-3 *AI-Based Precipitation Nowcasting Using Multi-Parameter Phased Array Weather Radar (MP-PAWR)*

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ゲリラ豪雨(局地的大雨)は、日本においてますます深刻な社会課題となっており、短い予測リードタイムであっても信頼性の高い警報を提供できる予測システムが求められている。この課題に対応するため、リモートセンシング研究室では3基のマルチパラメータ・フェーズドアレイ気象レーダー(MP-PAWR)を開発・配備し、高頻度かつ4次元(空間・時間)観測という他に類を見ない観測データを提供している。

本稿では、MP-PAWRデータと人工知能(AI)技術を活用してゲリラ豪雨を対象とした10分先の確率論的3次元降水予測(ナウキャスト)を実現する研究開発について紹介する。開発したナウキャストモデルは、MP-PAWRならではの観測能力を活かし、ゲリラ豪雨の発生予測において従来型レーダーを利用した手法を大幅に上回る性能を達成している。また、その実運用への実証として、株式会社MTIのスマートフォンアプリ「3D雨雲ウォッチ」を通じた豪雨警報の一般向け配信も行われている。

本報告では、まず従来手法の限界を概観した後、第5期中長期計画期間におけるシステムアーキテクチャとその発展について説明する。さらに、モデル出力の物理的解釈性、予測リードタイムおよび空間解像度の向上に向けた主要な課題を整理するとともに、第6期中長期計画において取り組む予定の実運用展開および社会実装に向けた今後の方向性について述べる。

Localized torrential rainfall (“guerrilla rain”) has become an increasingly serious societal challenge in Japan, requiring prediction systems capable of providing reliable warnings within very short lead times. In response to this need, the Remote Sensing Laboratory has developed and deployed three Multi-Parameter Phased-Array Weather Radar (MP-PAWR) which provide unique high-frequency 4D (space and time) observations.

This paper summarizes our ongoing efforts to apply artificial intelligence (AI) techniques to MP-PAWR data for probabilistic 3D prediction of guerrilla rainfall with a 10-minute lead-time (nowcast). Our nowcast model successfully exploits the unique capabilities of MP-PAWR, significantly outperforming conventional radar-based approaches in predicting the onset of guerrilla rainfall. Operational application is demonstrated through the public dissemination of heavy rainfall warnings from MTI Ltd.’s smartphone application “3D Amagumo Weather”. After reviewing the limitations of conventional approaches, we describe the system architecture and its evolution during the 5th Medium- to Long-Term Plan. Key challenges in advancing model interpretability, lead time, and spatial resolution are identified, along with future directions for operational deployment and societal applications, which will be addressed under the 6th Medium- to Long-Term Plan.

1 Introduction

In recent years, Japan has experienced an increase in short-duration heavy localized rainfall. These events,

commonly referred to as “guerrilla rainfall”, are convective storms which typically develop over only a few kilometers and last tens of minutes. Such storms can produce rainfall rates exceeding 50-100 mm h⁻¹, equivalent to several tons of

water per minute over an area of 100 m², resulting in flash floods, landslides, traffic disruption and casualties. Furthermore, climate change is expected to increase both the frequency and intensity of extreme events.

The societal impact of guerrilla rainfall is exacerbated by its low predictability. Unlike well-resolved regional precipitation driven by synoptic-scale systems (forcing scales exceeding 1,000 km), guerrilla rainfall is isolated, localized convective storms governed by rapid vertical development and highly non-linear dynamics. These characteristics strongly limit their predictability with standard numerical models and traditional short-term radar signal extrapolation (nowcasting) methods. Therefore, the improvement of nowcasting capabilities has become an urgent societal and scientific priority, even for very short lead-time of 10-20 minutes.

One of the missions of the Remote Sensing Laboratory of National Institute of Information and Communications Technology (NICT) is the development of advanced observation and information technologies to enhance disaster prevention and mitigation in Japan [1]. To address this challenge, NICT has developed an integrated strategy combining next-generation radar systems with artificial intelligence (AI). Building on more than a decade of experience with phased-array radar technology, three Multi-Parameter Phased-Array Weather Radars (MP-PAWR) are deployed in Saitama, Kobe, and Suita (Japan) [2][3]. These systems enable very rapid volumetric scanning of the atmosphere, helping to overcome limitations of conventional operational radars. During the 5th Medium- to Long-Term Plan period (FY2021–FY2025), NICT demonstrated an AI-based nowcasting real-time system with a lead time of 10 minutes. The target is the prediction of rapidly developing convective events, such as guerrilla rainfall, thereby addressing a critical limitation of existing operational systems.

This report presents both the observational framework and the AI-based nowcasting methodology developed at NICT. Section 2 reviews the main limitations of current operational prediction systems regarding guerrilla rainfall. Sections 3 and 4 describe the MP-PAWR units and the AI-based nowcasting developments at NICT. Finally, Section 5 summarizes these R&D activities and outlines future directions.

Limitations of Operational Precipitation Predictions

2.1 Ground-based precipitation radar

Ground-based weather radar is the most effective tool for observing precipitation with high spatio-temporal resolution (Fig. 1a, b) and plays a key role in operational prediction systems. The most common instruments operate in the C-band (~5 GHz) and X-band (~9 GHz). While higher frequency provides superior sensitivity to light rainfall and early-phase cloud droplets, it is more limited by signal attenuation in heavy precipitation. More critically, conventional operational radars rely on mechanical parabolic dishes to perform volume scans, typically one volume scan every ~5 minutes with ~10 elevation angles, which restrict the ability to resolve rapid vertical evolution associated with convective initiation and intensification (Fig. 1c). As a result, their ability to fully capture the rapid vertical development of guerrilla rainfall is limited.

In Japan, two complementary ground-based radar networks are widely used for precipitation monitoring. The Japan Meteorological Agency (JMA) operates a nationwide C-band radar network designed for broad coverage, providing precipitation measurement over the entire country with reliable calibration and long-term operational stability. This network is primarily optimized for large-scale monitoring and warning services. To enhance observations over urban areas, the Ministry of Land, Infrastructure, Transport and Tourism (MLIT) has deployed, in addition to

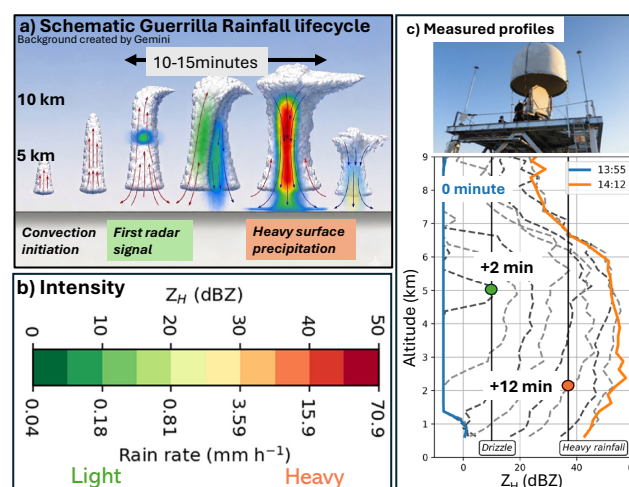


Fig. 1 a) Schematic lifecycle of a single-cell storm together with a X-band radar signal; The cloud base spans from 1 to 5 km. b) Approximated relationship between radar reflectivity and rainfall intensity; and c) Vertical profiles of reflectivity (Z_H) observed every 2 minutes on 1 August 2019 over Saitama with MP-PAWR, illustrating the rapid development prior to heavy surface precipitation.

its C-band network, the X-band polarimetric radar network (XRAIN). XRAIN allows for better detection of localized rainfall and urban flash-flood events. The use of polarimetric information further improves rainfall estimation accuracy and hydrometeor classification.

To overcome the spatio-temporal limitations of conventional scanning techniques, NICT and its partners have developed the Multi-Parameter Phased-Array Weather Radar (MP-PAWR), which can observe the three-dimensional structure of precipitation systems every 30 s using more than 100 elevation angles [2][3].

2.2 Numerical Weather Prediction (NWP) Model

Numerical Weather Prediction (NWP) models are the most advanced tools available for forecasting weather. They simulate the weather using physical laws to predict how the system will evolve over time. However, the atmosphere is inherently complex and chaotic. Small uncertainties in the atmospheric state, induced for example by small-scale processes not resolved by the model, can strongly influence the forecast. To reduce these errors, NWP models must frequently incorporate real-world observations (a process called data assimilation) to keep the model close to the actual atmospheric state. These observations, acquired from satellites and ground-based measurement networks, provide information on wind, clouds, thermodynamic and precipitation processes. While NWP models perform well for large-scale weather systems such as fronts and cyclones, they are less effective for predicting sudden, localized storms (e.g., guerrilla rainfall) for two main factors:

- Slow adjustment to new observations (spin-up time): After observations are assimilated, it takes time for their impact to propagate through the system. This issue limits the model's ability to respond to rapidly developing weather.
- Limited resolution: Even regional models typically use grid sizes of about one kilometer and time steps of several minutes. This is not sufficient to fully capture the rapid and small-scale processes involved in convective storms.

These limitations reduce the benefit of the high-frequency observations provided by MP-PAWR. To fully exploit the 30 s update cycle of the radar, RIKEN (Japan) has developed a reduced-spin-up data assimilation system that enables the effective use of rapidly acquired radar observations [4]. In the context of Expo 2025 Osaka, Kansai, Japan, a real-time demonstration has been successfully conducted with 500-m horizontal grid, 1000-member

ensemble [5][6]. However, such performance requires large computational resources of the supercomputer Fugaku and experience is limited to short-periods.

2.3 Nowcasting Methods

Precipitation nowcasting refers to very short-term forecasts, typically from a few minutes up to one hour, with high spatial resolution (<1 km). Radar-based methods are widely used to overcome the NWP limitations for short lead-time. These approaches extrapolate observed precipitation fields into the future using spatial motion vectors derived directly from consecutive radar data scans. Their primary strengths (✓) and limitations (△) are:

- ✓ Real-time applicability with very high spatial resolution of 250 m (e.g., RIKEN and JMA high-resolution systems).
- ✓ High prediction accuracy when precipitation evolution is primarily governed by advection (i.e., near-linear transport of existing precipitation structures).
- △ Limitation for representing precipitation intensity changes of convective growth and dissipation processes.

Consequently, while this approach performs well for mature, steady-state weather systems, it remains insufficient for predicting the initial growth of convective events like guerrilla rainfall. Representative methods include TREC (Tracking Radar Echoes by Correlation) and its 4D extensions developed in RIKEN (Japan) [7] which leverage MP-PAWR observations.

3 MP-PAWR: Toward a New Observation Paradigm for Weather Observation

3.1 Instrument and measured parameters

MP-PAWR is the result of long-term research and development conducted at NICT in collaboration with academic and industrial partners [2][3]. The very high spatio-temporal resolution of MP-PAWR (Subsection 3.2) is obtained by combining electronic beam steering in elevation with mechanical scanning in azimuth. These unique capabilities support research on very fast precipitation processes, as well as high-frequency data assimilation and nowcasting.

Three units, deployed at Kobe, Suita and Saitama, share similar specifications (Table 1). They operate in the X-band that allows better sensitivity to smaller precipitation particles than lower frequency (e.g., S- and C-band), but with

Table 1 Main characteristics of the MP-PAWR units deployed at Saitama, Suita (Osaka), and Kobe.

Site, Longitude, Latitude		Date	X-Band	Spatial Range	Cycle	Main parameters
Saitama University	139.6089° 35.86154°	2018	9.4 GHz $\lambda=3.2$ cm	$\sim 60 \times 60 \times 15$ km ³	30 s	Z _H : Horizontal Reflectivity [dBZ] Z _{DR} : Differential Reflectivity [dB] V _d : Doppler Radial Velocity [m s ⁻¹] Φ _{DP} : Differential phase (°) K _{DP} : Specific differential phase (°/km) Distributed by https://cumulon.jp/ [8]
Suita University	135.5228° 34.82334°	2024	9.7 GHz $\lambda=3.1$ cm	$\sim 80 \times 80 \times 15$ km ³		
Kobe NICT	134.9512° 34.71051°					

stronger attenuation. MP-PAWR measures polarimetric variables sensitive to hydrometeor type and microphysical processes which depend on how storms develop:

- Reflectivity (Z_H) indicates how intense the rainfall is. Stronger signals correspond to heavier rain or larger drops.
- Differential reflectivity (Z_{DR}) provides information about the shape of raindrops, which helps distinguish between rain types (e.g., stratiform, convective) and hydrometeor type and micro-physics: e.g., <0 for vertically oriented particles, ~ 0 dB: nearly spherical particles (small raindrops, hail) and >0 dB oblate drops (large raindrops).
- Doppler velocity (V_d) measures the motion of precipitation toward or away from the radar, giving insight into wind and storm dynamics.
- Specific differential phase (K_{DP}) is closely related to the amount of liquid water in the atmosphere and is particularly useful for accurately estimating heavy rainfall. It is particularly useful for estimating heavy rainfall because it is less sensitive to calibration errors and attenuation effects.
- Differential phase (Φ_{DP}) is the cumulative phase shift difference between horizontal and vertical polarizations along the propagation path. It is used to derive K_{DP} and helps correct attenuation and improve rainfall estimation during intense precipitation.

The MP-PAWR observations are freely distributed and visualize via the platform Cumulon (Preferred Networks, Inc. / NICT) [8]. This system uses advanced deep learning techniques to efficiently compress high-resolution radar data (350 Mbps without compression), enabling rapid transmission and practical use of large 3D observation datasets.

3.2 MP-PAWR and guerrilla rainfall prediction

MP-PAWR provides quasi-continuous observations of the vertical evolution of convective storms (Fig. 1c) which significantly enhance the information available for

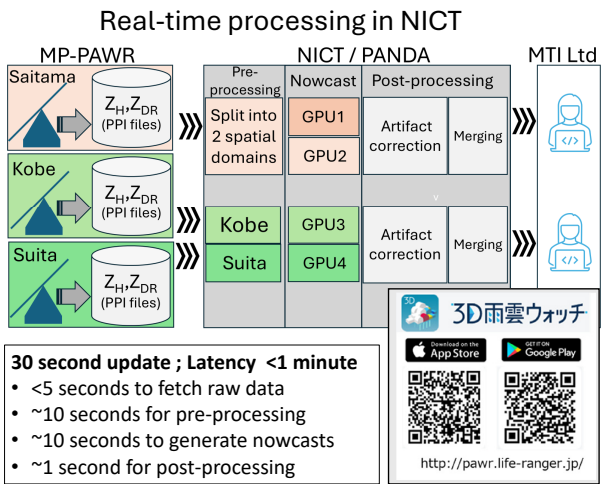


Fig. 2 Schematic view of the real-time processing chain utilizing the NICT's artificial network (ANN) based on the model (v1).

precipitation nowcasting compared with conventional weather radars. MP-PAWR can detect early signatures of convective development aloft 10–20 minutes before the onset of heavy rainfall at the surface (Fig. 1). This capability provides valuable lead time for decision-making and hazard mitigation in rapidly evolving situations such as guerrilla rainfall. However, as discussed in the previous section, conventional extrapolation-based nowcasting methods cannot reliably translate these early signals aloft into future rainfall intensity at the surface. Even the 4D TREC approach developed by RIKEN, which exploits the dense 3D MP-PAWR observations, remains fundamentally limited by its extrapolation-based method (e.g., no convective growth is considered).

To address this challenge, NICT has developed an AI-based system capable of predicting the onset of localized heavy rainfall near the surface with a lead-time of 10 minutes [9]. Version 1 (v1) is currently deployed in real-time using modest computing resources consisting of 2 servers equipped with 2 GPUs each [10]. Real-time data are fetched through NICT's PANDA platform. The nowcasts are used to generate alerts for localized heavy rainfall and deliver to the public through an MTI Ltd.'s smartphone

application (Fig. 2). This real-time system has also been evaluated during Expo 2025 Osaka, Kansai, Japan where it demonstrated its capability to provide early warnings of guerrilla rainfall events and received positive feedback from operational users [5]. However, several limitations of the current system have been noticed, especially when rainfall is mature or its evolution is primarily governed by motion rather than local convection.

4 AI-Based Nowcasting

4.1 Principle

Artificial Intelligence (AI), and in particular deep learning, provides a powerful framework for extracting patterns from high-dimensional and highly nonlinear datasets. Artificial Neural Networks (ANNs) can learn complex relationships between input and output variables directly from observations, without requiring an explicit description of the underlying physical processes. This characteristic makes them particularly attractive for precipitation nowcasting, where many of the processes governing convective initiation, growth, and dissipation are difficult to model accurately. In supervised learning, the ANN is trained using examples linking an input state at time T to the corresponding state at a future time $T+\Delta T$. The quasi-continuous MP-PAWR data are very well suited for this purpose because they comprehensively track the storm evolution through growth, maturation, and dissipation, under a wide range of meteorological conditions.

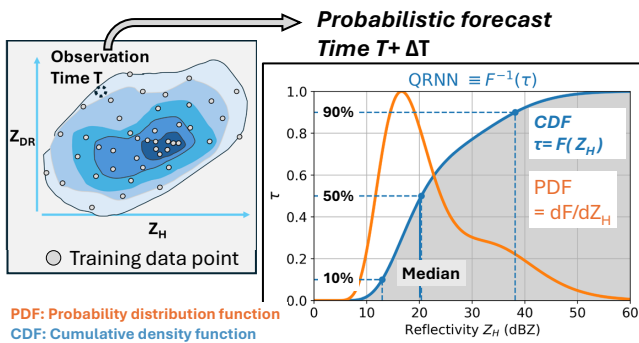


Fig. 3 Schematic illustration of probabilistic precipitation forecast with a Quantile Regression Neural Network (QRNN). QRNN processes radar observations at T to generate a forecast at $T+\Delta T$. It estimates the full conditional distribution, including the most likely state (e.g., median) and a prediction interval of possible nowcasts (grey area in right-side panel). This is achieved by predicting Z_H for specific quantile thresholds τ (e.g., 10, 50 and 90%), thereby providing a discrete sampling of the CDF. The real-time input may differ from historical training samples, as the NN generalizes across the learned data distribution.

However, multiple forecast outcomes may be consistent with a given input state. The spread of these outcomes depends not only on the intrinsic predictability of the atmospheric situation but also on the density of the training data surrounding the measurement state. A common approach is to estimate a single most likely outcome (e.g., median) using an appropriate loss function such as the L1 loss. This approach was adopted in v1, but for operational forecasting, it is important to estimate not only the most likely outcome but also the range of possible outcomes, particularly when the probability distribution function (PDF) is multi-modal. Fig. 3 illustrates this issue showing that the observation is linked to a bimodal distribution with a low but non-zero probability for heavy precipitation occurrence. Assessing the median state would simply predict low rainfall (20 dBZ). In v2, we introduced quantile regression to describe the forecast probability through multiple quantiles [11].

4.2 Model design

The model uses the recent evolution of volumetric radar observations to predict future rainfall conditions at a selected altitude level (Fig. 4a). Specifically, a 10-minute sequence of radar measurements, consisting of 20 samples acquired every 30 seconds, is used as input. Two radar variables (Z_H , Z_{DR}) are provided at 32 vertical levels with a

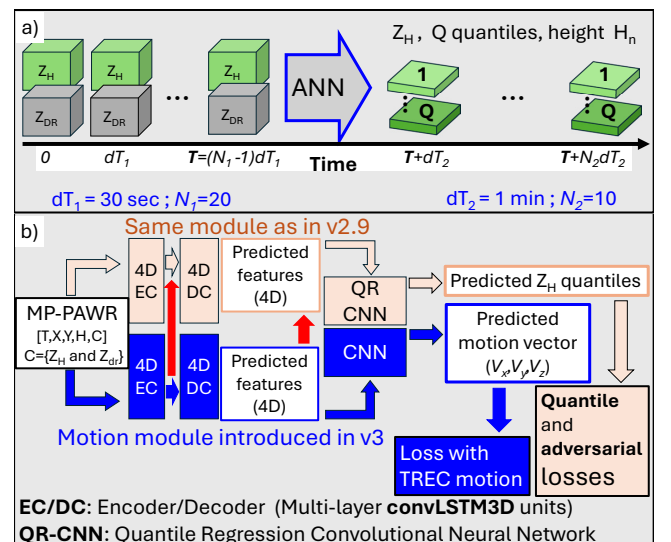


Fig. 4 Panel a) Processing flow through the ANN. The input parameters are sampled on a 3D grid of $0.5 \times 0.5 \times 0.25 \text{ km}^3$ resolution and 10-km vertical range. The predicted Z_H use the same horizontal coverage and resolution as the input. Panel b) Schematic of v3 under development. The orange blocks denote the precipitation module based on v2, while the blue blocks are the newly motion-guidance module introduced in v3. The tested model v2 contains about 15,000,000 trainable parameters.

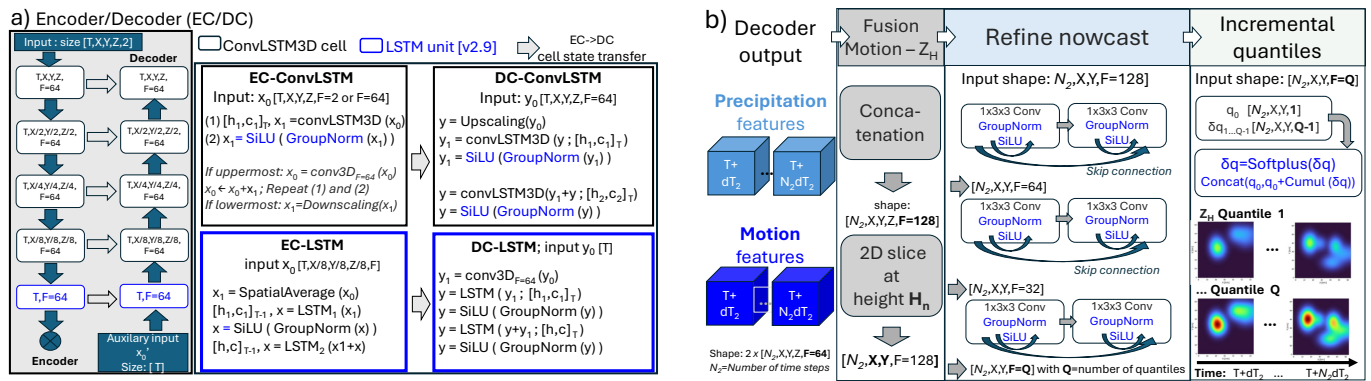


Fig. 5 Panel a): Encoder and decoder modules in v2.9/v3; Upgrades from version 2.0 are highlighted in blue (replacement of ReLU activation by SiLU and batch normalization by Group normalization). Panel b): Output quantile module introduced in v2 and upgraded for v3 with the integration of the motion and intensity fusion.

spacing of 250 m. The model relies exclusively on spatially invariant operations (i.e., convolutional layers without location-dependent parameters), and therefore the same trained model can be applied to any location and altitude. For instance, the model trained with Saitama data is successfully applied to Kobe and Suita. In the latest model version (v2.9), the prediction altitude is modified without changing the model instance, just by shifting the input vertical range [11]. Altitude dependent atmospheric conditions are learned during training (Subsection 4.3).

The model consists of two main components (Fig. 4b). The first component is an encoder–decoder (EC/DC) module that analyzes the spatiotemporal evolution of convective systems development in the observed volume and predicts their future (orange branch in Fig. 4b). It extracts latent features from the observations and propagates them forward in time. The EC/DC is built with ConvLSTM3D (Convolutional Long Short-Term Memory) units, which combine recurrent processing of temporal sequences with 3D spatial convolutions. It is organized as a 4-layer stack, with resolutions down-sampling from $0.5 \times 0.5 \times 0.25 \text{ km}^3$ at the upper layer to $4 \times 4 \times 2 \text{ km}^3$ at the deepest convLSTM3D layer (Fig. 5a). The receptive field, the volume that influences the predicted value in a pixel, is about $30 \times 30 \times 15 \text{ km}^3$. The DC output feeds a Quantile Regression CNN, which refines the prediction at the selected target altitude and generates the final rainfall quantile forecast (Fig. 5b).

4.3 Training

Training, i.e., model optimization, typically takes 4–5 weeks. It is an iterative process aimed at minimizing a loss function, which quantifies the mismatch between predicted and reference precipitation fields. The model parameters are updated with the widely used AdamW method after each

iteration using random batches of 64 samples (Fig. 7). A batch is a small subset of the training dataset, changed at each iteration.

In our implementation, convergence requires more than 70 passes through the entire dataset. The dataset consists of about 30,000 independent sequences, each covering 20 minutes of observations collected over Saitama during the summer of 2020. As illustrated in Fig. 3, the training space is typically sampled unevenly, resulting in a bias toward the densely populated regions associated with common cases. Consequently, the model tends to perform poorly on rare but important events, such as guerrilla rainfall. Hence, we restricted the data to summer months and down-sampled the light rain cases. While this resolves the under-sampling issue, it introduces a potential risk evaluated during testing: weak rainfall may be under predicted, increasing the false positive rate. Model generalization is improved with data augmentation techniques to artificially increase the diversity of motion cases. In addition, a random vertical shift of the input is applied to improve multi-altitude prediction capability [11]. Model performance is monitored through iterations using an independent validation dataset for stopping the iteration process before overfitting.

Training requires substantial GPU memory: ~35 GB for a $56 \times 56 \times 32$ input volume with a batch size of 1 and mixed precision (see below). This is significantly higher than inference (~10 GB) because backpropagation uses for gradient computation requires storing intermediate activations, gradients, and optimizer states. To decrease the memory consumption, the iterations are performed using mini batches (default size of 1) as described in Fig. 7a, and a reduced horizontal domain of $\sim 28 \times 28 \text{ km}^2$ (size of the receptive field). Training windows are automatically selected across the full radar domain using a clustering procedure

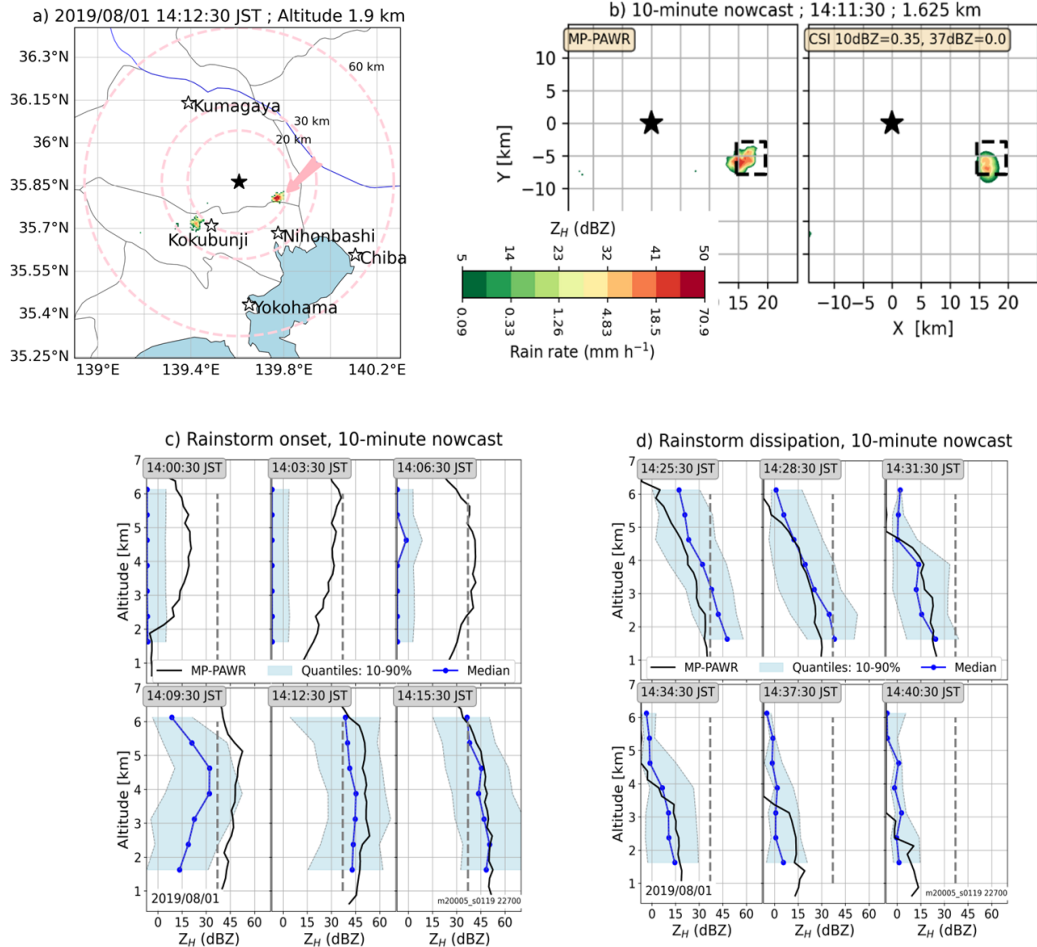


Fig. 6 Panel a) Guerrilla rainfall event (indicated by the pink arrow) observed on 1 August 2019 with Saitama MP-PAWR. Panel b) Same event measured with MP-PAWR (left side) and predicted with v2.9 (right-side). Panels c and d) Vertical profile development of the guerrilla rainfall event measured with MP-PAWR (black lines) and predicted (blue dot-lines) during the storm onset and dissipation phases, respectively. The light-blue regions show the 10-90% quantile range. The vertical dash-lines indicate the heavy-rainfall threshold (37 dBZ).

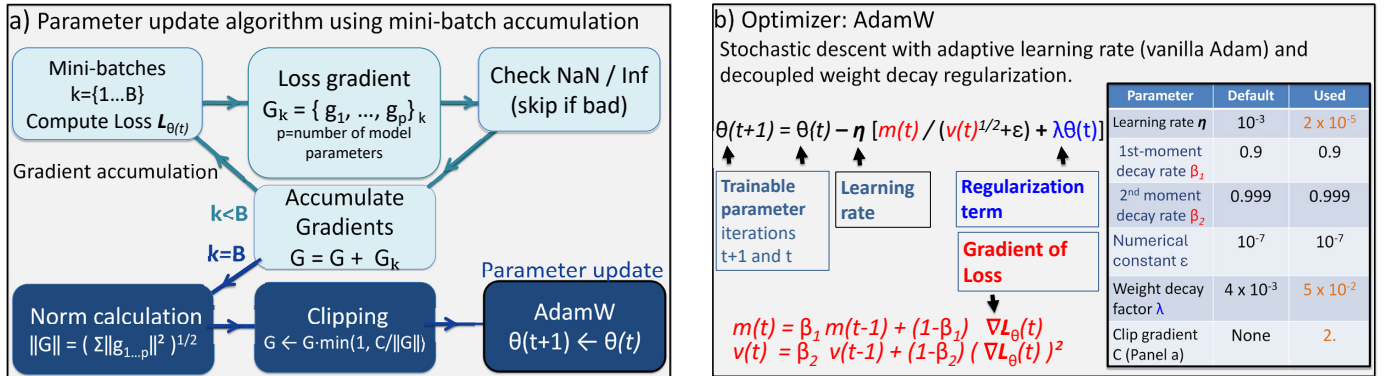


Fig. 7 Training strategy. Panel a) Mini-batch accumulation scheme: gradients are computed over mini-batches, checked for numerical instability and accumulated before parameter update. This allows a larger effective batch size of 64 while limiting GPU memory usage. Panel b) AdamW equation for updating model parameters.

that identifies regions containing precipitation at the nowcast altitude in the first, middle, or last frame of each 20-minute sequence. Mixed-precision is used to further reduce memory usage: Computationally intensive convolutions are performed using 16-bit brain floating-point precision (bfloat16), while numerically sensitive

components (activation and normalization) are maintained in 32-bit precision. However, this method introduces numerical instabilities, necessitating the handling of non-finite values during gradient computation (Fig. 7a).

The model v1 was trained using a pixel-wise L1-norm loss function, leading to the prediction of the median of the

possible nowcasts. To improve fine spatial structures, a perturbation-based training strategy inspired by Generative Adversarial Networks (GANs) was successfully applied [9]. With the transition to probabilistic forecasting (v2) through quantile regression, the L1-norm was replaced by the pinball loss function, not readily compatible with the adversarial technique [11], requiring the development of a new method to preserve realistic spatial correlations of the probabilistic outputs.

4.4 Current R&D

We target operational deployment and, for this purpose, nowcasting must be reliable, interpretable, and computationally efficient. For this end, the model is being reshaped to improve performance across a wider range of weather regimes, particularly in cases where advection (motion) dominates rainfall evolution. The new model (v3) adopts a more physically interpretable framework by combining two specialized units: 1) a 3D motion prediction unit, and 2) a precipitation unit dedicated to intensity probabilistic prediction conditioned by motion field (Fig. 4b). The motion unit learns motion vector generated by the RIKEN's TREC model (see Subsection 2.3) which has been deployed in NICT. Motion information is explicitly transmitted to the precipitation intensity prediction module. However, the training strategy requires further refinement to determine whether precipitation prediction errors should be backpropagated to the motion estimation module, or whether the two components should be optimized independently.

This structure mimics the physical equation separating the advection component from the source-sink term, enhancing model interpretability and may improve the representation of these distinct physical processes. Furthermore, the hybrid framework facilitates the future integration of additional constraints or data sources into each component independently.

4.5 Collaborations

Since the initial development phase of this project, we have established active collaborations with Osaka University, Chiba University, and RIKEN, as well as with Chalmers in Sweden. These collaborations have contributed to a deeper understanding of radar observations and supported the integration of rapidly evolving machine learning techniques into our system. Such exchanges are essential for maintaining scientific relevance and accelerating innovation, and they will be further strengthened to support the next development

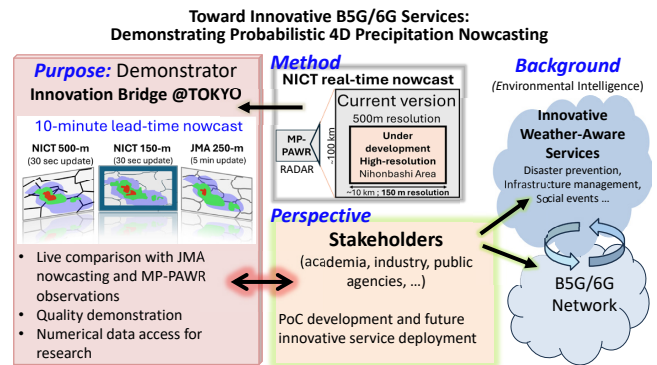


Fig. 8 Toward Societal application of our nowcasts. Potential stakeholders will be engaged through the demonstration of the nowcast capability leveraging “Innovation Bridge@Tokyo” (IBT) facility created by NICT.

phases.

Within NICT, discussions have also started with the Beyond Connectivity Design Initiative unit to promote and demonstrate our real-time nowcasting capabilities. As part of this effort, we plan to deploy a live demonstration of the system at the “Innovation Bridge@TOKYO” facility, showcasing its potential for real-time applications and fostering engagement with external stakeholders (Fig. 8).

5 Conclusion and Future Steps

The combination of MP-PAWR developed at NICT (and partners) with AI has demonstrated strong potential for real-time very short-term prediction of “guerrilla rainfall”, with a lead time of 10 minutes. MP-PAWR enables the early detection of convective initiation aloft (typically at 4–6 km altitude), while the AI model successfully extrapolates this signal to the surface, capturing the possible onset of heavy rainfall. This synergy outperforms operational systems based on conventional observational and nowcast approaches.

In the 6th Medium- to Long-Term Plan (FY2026-FY2031), our objectives are to further advance the current system toward a more robust and operationally relevant framework for early warning and weather-aware applications, especially in urban areas. Specifically, we aim to: (i) improve the calibration of probabilistic (quantile) outputs to provide reliable rainfall occurrence probabilities, (ii) extend the prediction lead-time to approximately 20 minutes, (iii) better characterize spatial correlation between quantiles to ensure spatially consistent precipitation fields, and (iv) improve the spatial resolution down to ~200 m, matching the native capabilities of MP-PAWR. Achieving these goals

requires the integration of additional real-time observational data to better constrain the early stages of convective development (Fig. 1). Infrared observations from the geostationary satellite Himawari will be used to complement MP-PAWR, and new methods will be developed for fusing heterogeneous datasets with different physical content, dimensionality and spatial and temporal sampling. New AI-based post-processing techniques based on copula methods will be explored to improve the spatial coherence of the predicted precipitation probability density functions.

Another key objective is to initiate and strengthen collaborations with external partners to develop practical applications of our nowcasting system. We aim to explore innovative weather-aware services for 5G and Beyond-5G (B5G) communication systems, where high-resolution, short-term rainfall forecasts can support network optimization, resilience, and adaptive resource management under rapidly changing atmospheric conditions.

Finally, let's note that the proposed framework can be readily adapted to next-generation observing systems, including the advanced C-band phased-array radar currently under consideration at NICT, as well as satellite-based observations.

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