



Introducing a Discrete Multi-beam CubeSat Radar for Global Precipitation Observations: Conceptual Demonstration and AI-powered 3D Reflectivity Reconstruction

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Abstract. Current spaceborne precipitation radars, including the Global Precipitation Measurement Dual-frequency Precipitation Radar and the FengYun-3G Precipitation Measurement Radar (FY-3G PMR), provide unique three-dimensional (3D) observations of global precipitation systems. However, limited spatiotemporal sampling and relatively long revisit intervals constrain the monitoring of rapidly evolving storms. This study proposes a discrete multi-beam precipitation radar concept for small-satellite constellations and develops a radar-constrained active–passive inpainting framework for reconstructing unsampled inter-beam observations. Collocated FY-3G PMR reflectivity and Microwave Radiation Imager for the Rainfall Mission (MWRI-RM) brightness temperatures observed from the same platform are used to emulate sparse radar sampling. The proposed model integrates sparse radar reflectivity and 26 passive microwave channels within a squeeze-and-excitation U-Net. Independent experiments are conducted for the PMR Ku- and Ka-band observations under different beam-spacing configurations. Reconstruction performance is evaluated exclusively within the masked inter-beam regions, and a boundary-smoothness constraint promotes continuity between reconstructed and observed beams. Channel-ablation experiments are further used to diagnose model sensitivity to individual passive microwave channels. The results demonstrate that sparse radar profiles and passive microwave observations can jointly recover coherent 3D reflectivity structures over a range of sampling densities. Across both radar frequencies, the overall mean absolute error and error standard deviation remained below approximately 2.0 and 3.0 dB, respectively, across configurations in which one to five beams were skipped between adjacent retained beams. The dependence of reconstruction accuracy on beam spacing provides quantitative guidance for balancing beam number, cross-track sampling extent, and constellation cost, while the channel-sensitivity results inform the design of future active–passive payloads. The proposed framework also provides a transferable basis for retrieval and reconstruction algorithms for future sparse-sampling radar missions.



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1 Introduction

Precipitation is a fundamental component of the Earth's water and energy cycles and represents the primary source of fresh-water for natural ecosystems and human society (Michaelides et al., 2009; Skofronick-Jackson et al., 2017). Its strong spatial and temporal variability creates a continuing need for observations that can support weather forecasting, climate diagnostics, hydrological applications, and disaster risk reduction (Hou et al., 2014; Kidd et al., 2021; Su et al., 2026). Although rain gauges, disdrometers, and ground-based weather radars provide valuable in situ and regional measurements, their spatial coverage is geographically uneven and remains limited over oceans, complex terrain, polar regions, and other data-sparse areas (Tapiador et al., 2012). Satellite observations are therefore essential for monitoring precipitation on a global and consistent basis. Existing satellite precipitation observing systems include visible and infrared sensors, passive microwave radiometers, and active radars (Stephens and Kummerow, 2007; Kidd and Levizzani, 2011). Nevertheless, direct information on the vertical structure of precipitation, including storm depth, melting-layer height and hydrometeor profiles, is primarily provided by active radar measurements (Le and Chandrasekar, 2013; Liu and Zipser, 2015; Li and Moiseev, 2019; Hu et al., 2024). Spaceborne precipitation radars thus offer a unique three-dimensional (3D) measurement capability for precipitation systems and remain a critical component of the global satellite precipitation observing constellation (Battaglia et al., 2020).

Since the launch of the Tropical Rainfall Measuring Mission (TRMM), spaceborne precipitation radars have substantially advanced the observation and understanding of precipitation systems (Liu et al., 2024, 2025). The TRMM Precipitation Radar (PR) was the first spaceborne precipitation radar to provide 3D information on storm structure (Kummerow et al., 1998). This capability was subsequently extended by the Global Precipitation Measurement Core Observatory (GPM-CO), which carries the Ku- and Ka-band Dual-frequency Precipitation Radar (DPR) and provides dual-frequency constraints on precipitation microphysics (Hou et al., 2014; Ni et al., 2019). More recently, the FengYun-3G (FY-3G) satellite was launched with the Ku- and Ka-band Precipitation Measurement Radar (PMR), further expanding the global record of spaceborne precipitation radar measurements with wider swath and better sensitivity (Zhang et al., 2023; Shang et al., 2026). Together, these missions have provided critical observational datasets and benchmarks for precipitation science, retrieval algorithm development, numerical weather prediction evaluation, and climate studies (Fu et al., 2017; Chase et al., 2025; Kubota et al., 2025).

Despite these achievements, the operational use of spaceborne precipitation radars remains limited by sparse temporal sampling. Existing precipitation radar missions sample any given location only intermittently because of finite swath widths and orbital revisit constraints. Although temporal sampling could, in principle, be improved by deploying constellations of conventional cross-track scanning precipitation radars, such an approach would require substantial resources owing to demanding requirements on payload complexity, antenna configuration, and mission cost. Alternative observing architectures are therefore needed to improve the temporal sampling of 3D precipitation measurements while maintaining feasible payload and constellation designs.



The successful demonstration of RainCube (Radar in a CubeSat), a miniaturized Ka-band precipitation profiling radar implemented on a 6U CubeSat platform, has demonstrated the feasibility of compact, low-cost, and rapidly deployable spaceborne precipitation radar payloads (Peral et al., 2019; Sy et al., 2022). This technological development has motivated emerging small-satellite precipitation observing concepts, including commercial constellations with active radar and passive microwave sensors (Roy et al., 2023) and the NASA INvestigation of Convective UpdraftS (INCUS) mission (Haddad and Sy, 2024). However, a constellation composed only of single narrow-beam nadir-pointing radars would still require a large number of satellites to achieve both frequent temporal sampling and adequate spatial coverage. This limitation motivates a new intermediate observing concept proposed in this study: a discrete multi-beam precipitation radar (MPR) that intentionally replaces continuous cross-track scanning with a small set of fixed beams and uses data-driven reconstruction to recover the missing inter-beam precipitation structures (see Fig. 1 for detail). The proposed configuration aims to provide a practical compromise between single narrow-beam profilers and fully scanning or electronically steered wide-swath radars by increasing cross-track sampling information while retaining a simplified, low-resource payload architecture.

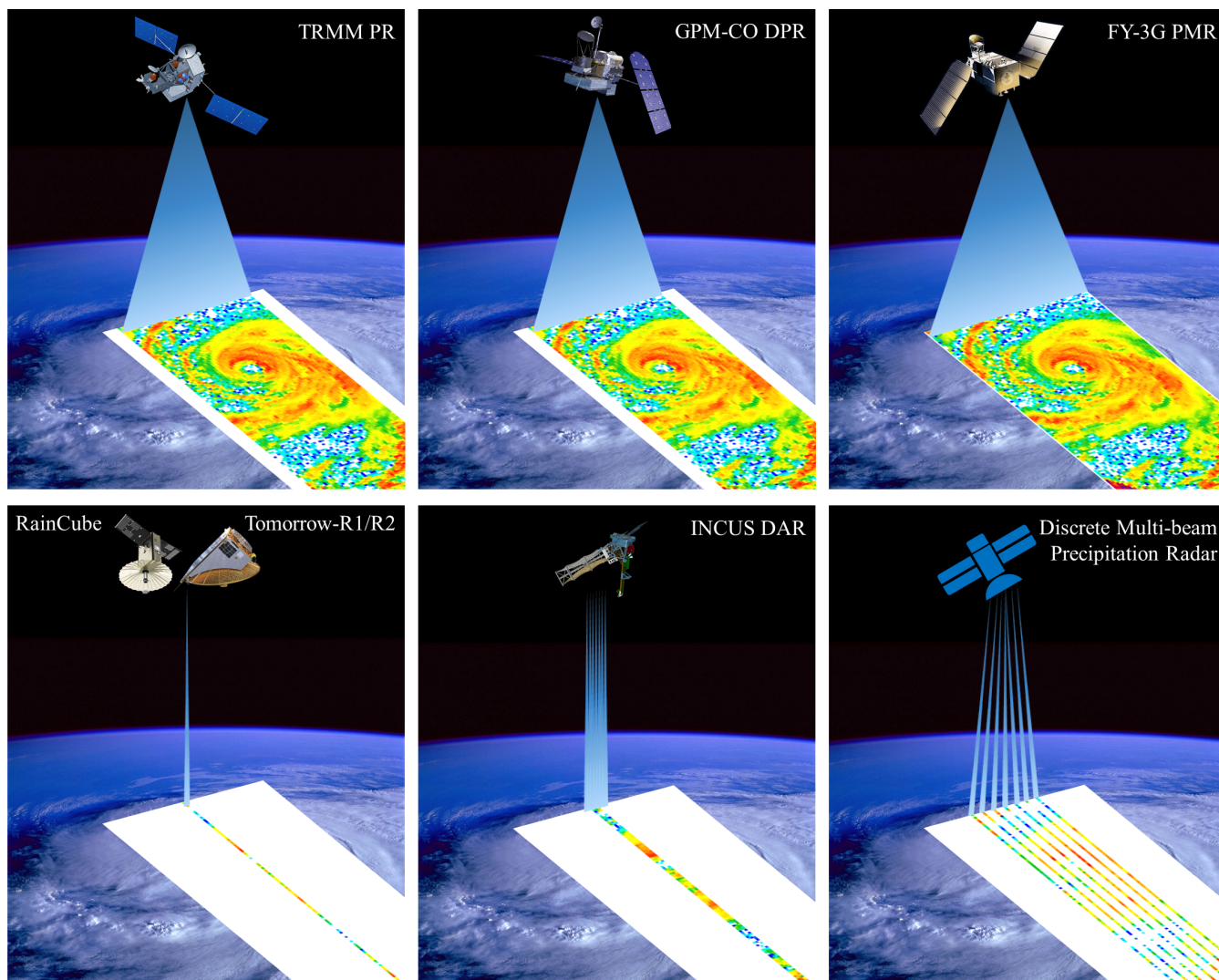


Figure 1. Representative observation geometries and cross-track sampling extents of selected spaceborne precipitation radars. The TRMM PR and the GPM DPR employ electronically scanned phased-array antennas with 49 cross-track beams, providing swath widths of approximately 215 and 245 km, respectively. The FY-3G PMR uses an electronically scanned phased-array antenna with 59 cross-track beams to cover a swath of approximately 303 km. RainCube is a single-beam, near-nadir-pointing Ka-band profiling radar with a footprint of approximately 8 km, whereas the fixed, non-scanning Ka-band radars aboard Tomorrow-R1 and Tomorrow-R2 provide a horizontal resolution of approximately 4.5 km. The Dynamic Atmospheric Radar (DAR) of the INCUS mission employs seven strongly overlapping cross-track beams to sample an approximately 10 km swath. The multi-beam precipitation radar (MPR) proposed in this study uses a small number of widely separated beams to span a cross-track observation envelope exceeding 100 km. The unsampled inter-beam regions are reconstructed using the radar-constrained active–passive deep-learning inpainting framework developed in this study. The dimensions shown are approximate, and the schematic is not drawn to scale.



The central challenge introduced by the discrete multi-beam concept is the presence of unobserved gaps between adjacent
65 radar beams. These gaps lead to incomplete cross-track reflectivity fields and may limit the direct operational use of the
observations. Recent advances in machine learning provide a promising pathway for addressing this problem, although existing
radar-like precipitation reconstruction studies differ in the observational constraints they exploit. One group of studies has used
geostationary satellite observations to estimate synthetic or proxy radar reflectivity (Hilburn et al., 2021; Xue et al., 2026).
These approaches benefit from high temporal sampling and broad spatial coverage, but they mainly infer horizontal radar-
70 like products from cloud-top and lightning information and do not directly provide vertically resolved radar reflectivity. A
second group of studies has reconstructed pseudo-radar precipitation structures from passive microwave observations (Yang
et al., 2024, 2025; Morvais and Liu, 2026). Passive microwave measurements are physically sensitive to precipitation through
hydrometeor emission and scattering, however, when used alone, they provide indirect and vertically integrated constraints,
leaving the reconstruction of fine-scale vertical structures and localized reflectivity features underconstrained in the absence
75 of in-scene radar observations. A third and more closely related line of work is radar missing data completion or inpainting
(Geiss and Hardin, 2021; King et al., 2024). Inpainting explicitly preserves available radar measurements and uses them as
direct constraints for estimating missing regions, making it well suited to the discrete multi-beam problem considered here,
where true radar profiles are available at selected cross-track beams and only the inter-beam regions need to be reconstructed.
This study therefore formulates discrete-beam reconstruction as a radar-constrained inpainting problem within a spaceborne
80 active–passive fusion framework (Sun et al., 2016), in which sparse radar reflectivity profiles define the observed precipitation
structure and passive microwave brightness temperatures provide complementary information for filling the inter-beam gaps.

This formulation requires a model that can simultaneously exploit the spatial continuity of radar reflectivity, preserve the
information contained in the observed radar beams, and integrate complementary passive microwave measurements. U-Net
provides a suitable basis for this task because its encoder–decoder structure captures multiscale precipitation morphology,
85 while skip connections help retain fine-scale spatial details during reconstruction (Ronneberger et al., 2015). These properties
are important for precipitation reflectivity fields, which often contain both coherent mesoscale organization and localized
convective or stratiform features (Chase et al., 2023). In the present active–passive reconstruction problem, passive microwave
brightness temperatures provide additional information related to hydrometeor emission, scattering, and column-integrated
precipitation properties (Kummerow et al., 2001). To better exploit these multichannel inputs, this study further incorporates
90 a squeeze-and-excitation (SE) channel attention mechanism, which adaptively recalibrates channel-wise feature responses by
modelling inter-channel dependencies (Hu et al., 2018). The resulting SE-U-Net framework is therefore designed to reconstruct
inter-beam radar reflectivity gaps by combining sparse but physically direct radar constraints with complementary passive
microwave information.

In this study, we propose a discrete multi-beam spaceborne precipitation radar concept and develop a radar-constrained
95 active–passive inpainting framework to reconstruct unsampled inter-beam observations. Using collocated radar reflectivity and
passive microwave brightness temperatures, sparse cross-track radar sampling is emulated by selectively masking radar beams,
and a U-Net-based model with SE channel attention is trained to reconstruct the complete cross-track–vertical reflectivity
field. The objectives of this study are to (1) formulate the reconstruction problem for discrete multi-beam precipitation radar



observations, (2) integrate sparse radar reflectivity and passive microwave measurements within an SE-U-Net reconstruction framework, (3) quantify reconstruction performance under different beam-spacing configurations, and (4) assess the sensitivity of the reconstruction to individual input channels. Section 2 describes the data, Section 3 presents the active–passive matching and reconstruction methodology, Section 4 reports the reconstruction performance and channel-sensitivity results, and Section 5 discusses the implications, limitations, and applicability of the proposed framework to future spaceborne cloud and precipitation radar missions.

2 Data

The data used in this study were obtained from the PMR and the MicroWave Radiation Imager for the Rainfall Mission (MWRI-RM) onboard the FY-3G satellite. FY-3G is the first of two planned dedicated precipitation satellites in the second generation of China’s FY-3 polar-orbiting meteorological satellite program. It operates in an inclined orbit with a nominal altitude of 407 km and an inclination of 50°, and was specifically designed to observe the 3D structure of precipitation systems in the mid and low latitudes (Zhang et al., 2023, 2025).

The FY-3G PMR is composed of a Ku-band radar (13.35 GHz) and a Ka-band radar (35.55 GHz). With the horizontal resolution at nadir of about 5 km, both Ku- and Ka-band radars have 59 cross-track beams and a swath width of approximately 303 km. The nominal sensitivities of the Ku- and Ka-band radars are approximately 18 dBZ and 12 dBZ, respectively. Based on storm top observations, Liu et al. (2025) reported minimum detectable reflectivity values of 12.03 dBZ for the PMR Ku-band radar and 8.60 dBZ for the PMR Ka-band radar. The vertical sampling interval of PMR is 50 m. The PMR data used here is FY-3G PMR Level 1 product version 01.

The FY-3G MWRI-RM is a conically scanning total-power microwave radiometer and represents an improved version of the MWRI instrument onboard the predecessor of the FY-3 series. It includes 17 frequencies and 26 channels ranging from 10 to 183 GHz. These channels include 9 dual-polarized window channels between 10 and 89 GHz, 12 oxygen absorption sounding channels near 50 and 118 GHz, and water-vapor sounding channels near 183 GHz for atmospheric temperature and humidity profiling (Zhang et al., 2023). The dual oxygen absorption bands provide several advantages for precipitation remote sensing, including improved sensitivity to weak precipitation over land and information related to the location and thickness of the melting layer. The additional sounding channels near the 183 GHz water-vapor absorption line further enhance the capability of MWRI-RM to characterize atmospheric humidity and precipitation structures. MWRI-RM has an effective observation swath of approximately 800 km, and its spatial resolution varies with frequency, ranging from about 5 to 25 km (Yang et al., 2025; Han et al., 2026). The MWRI-RM data used here is FY-3G MWRI-RM Level 1 product version 01.



3 Methods

3.1 Problem formulation and experimental design

This study formulates discrete multi-beam precipitation radar reconstruction as a radar-constrained active–passive inpainting
130 problem. The objective is to recover the complete cross-track–vertical reflectivity field from sparse radar observations and
collocated passive microwave brightness temperatures. The radar beams provide direct constraints on precipitation structure,
while the passive microwave measurements supply complementary information on hydrometeor emission and scattering (Kum-
merow et al., 2001; Skofronick-Jackson et al., 2017). The experiments represent a sampling-level emulation of the proposed
observing concept and therefore assess the recoverable information from discrete cross-track sampling rather than the full
135 antenna, sensitivity, and noise characteristics of a future instrument.

The reconstruction framework was evaluated separately using the PMR Ku- and Ka-band observations under an identical ex-
perimental protocol. For radar band $b \in \{\text{Ku}, \text{Ka}\}$, let $Z^{(b)}$ denote the reflectivity field in physical units and $Z'^{(b)}$ its normalized
representation defined in Section 3.4. The reconstruction target is

$$\mathbf{Y}^{(b)} = Z'^{(b)} \in \mathbb{R}^{1 \times W \times H}, \quad (1)$$

140 where $W = 25$ is the number of cross-track positions and $H = 300$ is the number of vertical bins. The spatial dimensions
are ordered as cross-track followed by vertical. For beam-spacing configuration n , the normalized model input comprises, in
order, complete reflectivity as the first channel, the binary beam-availability mask as the second channel, and 26 brightness-
temperature channels:

$$\mathbf{X}^{(b,n)} = [Z^{(b,n)}, M_n, T'_1, T'_2, \dots, T'_{26}] \in \mathbb{R}^{28 \times W \times H}, \quad (2)$$

145 and the reconstruction model predicts the complete normalized field as

$$\hat{\mathbf{Y}}^{(b,n)} = f_{\theta}^{(b,n)}(\mathbf{X}^{(b,n)}). \quad (3)$$

Here, $M_n = 1$ denotes a retained, available radar beam and $M_n = 0$ denotes an unobserved beam position. Independent models
were trained for each radar band and each of the five beam-spacing configurations ($n = 1-5$).

3.2 Matched active–passive sample construction

150 The reconstruction samples were constructed by collocating FY-3G PMR measured reflectivity factor (Z_m) with MWRI-RM
brightness temperatures (T_b). Although the full PMR swath contains 59 cross-track beams, only the central 25 beams were
retained for model development and evaluation. This selection reduces sampling and geometric differences near the swath
edges while preserving an effective cross-track span exceeding 100 km, which is representative of a feasible swath width for
the proposed discrete multi-beam radar configuration.

155 The Z_m sections were selected according to the following criteria. First, precipitation had to be detected for all 25 central
beams, as indicated by `flagPrecip` $\neq 0$ in the PMRL1 data. Second, all selected beams were required to be located over



ocean surfaces, corresponding to `landSurfaceType = 0`. Third, the reflectivity profiles were extracted from altitudes below 15 km. Range bins affected by surface clutter, extending from the clutter-free bottom (`binClutterFreeBottom`) to the sea surface, were assigned missing values (NaN). After vertical extraction, each radar reflectivity section contained 300 vertical bins.

The PMR reflectivity sections were subsequently collocated with the MWRI-RM brightness temperatures in both time and space. For each PMR reflectivity column, the MWRI-RM footprint with the smallest temporal and geographical separation was selected. The resulting matched brightness temperatures formed a one-dimensional cross-track array, which was replicated along the vertical dimension to conform to the cross-track–vertical grid of the radar reflectivity section. Each matched sample therefore contained a radar reflectivity field of size 25×300 (cross-track $\times$ vertical) and 26 collocated MWRI-RM brightness-temperature channels represented on the same grid. The detailed collocation procedure is illustrated in Fig. 2.

The Ku- and Ka-band reflectivity fields were processed independently using the same collocation and sample-construction procedure. In this study, collocated FY-3G PMR and MWRI-RM observations acquired between August 2023 and August 2024 were used to construct the matched active–passive dataset, yielding a total of 286279 Ku-band samples and 297504 Ka-band samples. For each frequency band, the corresponding PMR reflectivity section was used as the reconstruction target, whereas the same set of collocated MWRI-RM brightness-temperature channels served as the passive microwave input. The final model input consisted of radar reflectivity, a beam-availability mask, and the 26 MWRI-RM brightness-temperature channels as listed in Tab. 1.

Two complete matched orbits were reserved as an independent test set and were also used for the case-study evaluation. After excluding these orbits, the remaining samples were divided into training and validation subsets at a ratio of 8:2. The same fixed partition was used for all beam-spacing configurations to ensure consistent comparisons.

3.3 Sparse discrete-beam simulation

To emulate discrete multi-beam sampling, selected cross-track beams were retained from each complete PMR reflectivity section, while the remaining beam positions were treated as unobserved. A vertically invariant binary beam-availability mask $M_n \in \{0, 1\}^{W \times H}$ was defined for each beam-spacing configuration.

For the 25-beam cross-track domain, the central beam (beam 13) was always retained. For each beam-spacing configuration, the retained beams were defined as

$$M_n(i, j) = \begin{cases} 1, & \text{if } |i - 13| \bmod (n + 1) = 0, \\ 0, & \text{otherwise,} \end{cases} \quad (4)$$

where n denotes the number of skipped PMR beams between adjacent retained beams. Five configurations ($n = 1$ –5) were examined, as summarized in Table 2.

The sparse radar input was generated as

$$Z_{\text{sparse}}^{(b, n)} = M_n \odot Z^{(b)} + (1 - M_n) \odot (-1), \quad (5)$$

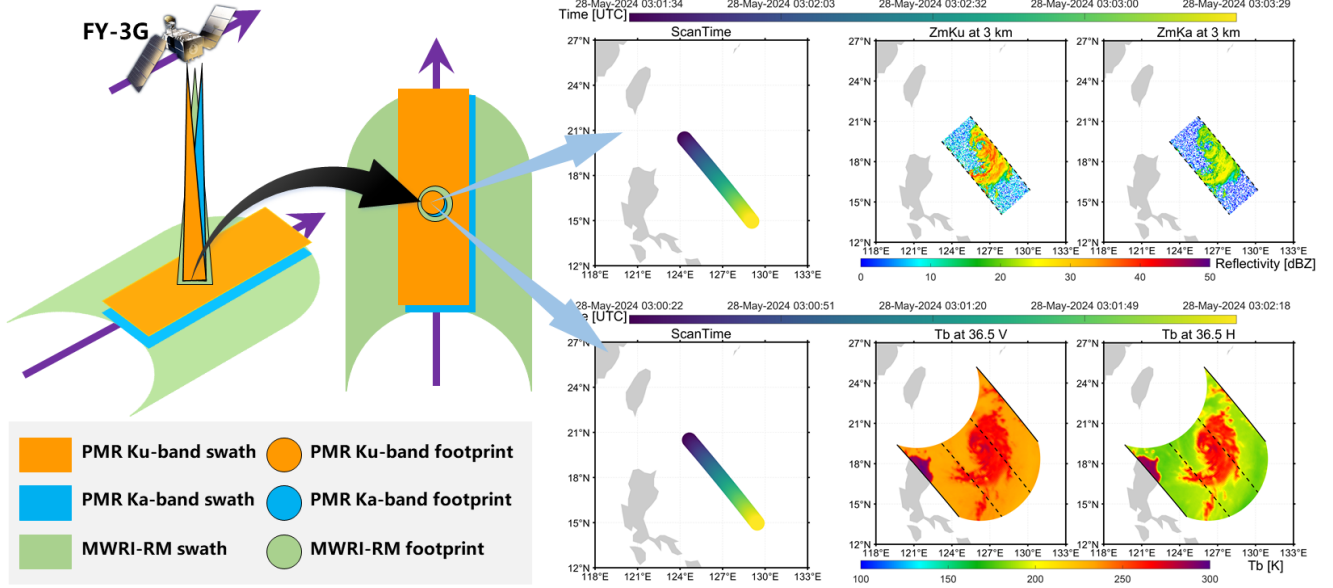


Figure 2. Collocation of FY-3G PMR and MWRI-RM observations. The left panel illustrates the swaths and footprints of Ku-band radar, Ka-band radar and MWRI-RM. The right panels show an example observed on 28 May 2024, including PMR Ku- and Ka-band measured reflectivity factor at 3 km altitude, MWRI-RM brightness temperatures at 36.5 GHz in vertical and horizontal polarization, and the corresponding scan times. The dimensions shown are approximate, and the schematic is not drawn to scale.

where $Z'^{(b)}$ is the normalized reflectivity field and $\odot$ denotes element-wise multiplication. Because -1 also corresponds to the normalized lower bound of valid reflectivity, the beam-availability mask distinguishes unobserved positions from valid low-reflectivity values. Only the radar reflectivity channel was masked, all passive microwave brightness-temperature channels were retained over the full domain.

3.4 Input normalization and model input

Radar reflectivity was clipped to 0–60 dBZ and linearly normalized to $[-1, 1]$:

$$Z' = 2 \frac{\text{clip}(Z, Z_{\min}, Z_{\max}) - Z_{\min}}{Z_{\max} - Z_{\min}} - 1, \quad (6)$$

where $Z_{\min} = 0$ dBZ and $Z_{\max} = 60$ dBZ.

The MWRI-RM brightness temperatures were standardized channel by channel using statistics calculated from the training set:

$$T'_c = \frac{T_c - \mu_c}{\sigma_c}, \quad c = 1, 2, \dots, 26, \quad (7)$$

where μ_c and σ_c are the training-set mean and standard deviation of channel c , respectively.



Table 1. Composition and fixed order of the 28-channel model input.

No.	Label	Channel
1	Z_m	PMR measured radar reflectivity factor
2	M_n	Binary beam-availability mask (1: retained, 0: unobserved)
3	Tb_{01}	Tb , 10.65 GHz, V polarization
4	Tb_{02}	Tb , 10.65 GHz, H polarization
5	Tb_{03}	Tb , 18.7 GHz, V polarization
6	Tb_{04}	Tb , 18.7 GHz, H polarization
7	Tb_{05}	Tb , 23.8 GHz, V polarization
8	Tb_{06}	Tb , 23.8 GHz, H polarization
9	Tb_{07}	Tb , 36.5 GHz, V polarization
10	Tb_{08}	Tb , 36.5 GHz, H polarization
11	Tb_{09}	Tb , 89.0 GHz, V polarization
12	Tb_{10}	Tb , 89.0 GHz, H polarization
13	Tb_{11}	Tb , 50.30 GHz, V polarization
14	Tb_{12}	Tb , 50.30 GHz, H polarization
15	Tb_{13}	Tb , 52.61 GHz, V polarization
16	Tb_{14}	Tb , 52.61 GHz, H polarization
17	Tb_{15}	Tb , 53.24 GHz, V polarization
18	Tb_{16}	Tb , 53.24 GHz, H polarization
19	Tb_{17}	Tb , 53.75 GHz, V polarization
20	Tb_{18}	Tb , 53.75 GHz, H polarization
21	Tb_{19}	Tb , 118.7503 ± 3.2 GHz, V polarization
22	Tb_{20}	Tb , 118.7503 ± 2.1 GHz, V polarization
23	Tb_{21}	Tb , 118.7503 ± 1.4 GHz, V polarization
24	Tb_{22}	Tb , 118.7503 ± 1.2 GHz, V polarization
25	Tb_{23}	Tb , 165.5 ± 0.75 GHz, V polarization
26	Tb_{24}	Tb , 183.31 ± 2.0 GHz, V polarization
27	Tb_{25}	Tb , 183.31 ± 3.4 GHz, V polarization
28	Tb_{26}	Tb , 183.31 ± 7.0 GHz, V polarization

200 The resulting data-preparation workflow is summarized in Fig. 3a. The normalized radar reflectivity, beam-availability mask, and 26 brightness-temperature channels were assembled into the model input, while the complete normalized reflectivity field was used as the reconstruction target, following Eqs. (2) and (1).

**Table 2.** Sparse-beam configurations for the 25-beam cross-track domain.

n	Retained beams	Retained-beam indices
1	13	1, 3, 5, 7, 9, 11, 13, 15, 17, 19, 21, 23, 25
2	9	1, 4, 7, 10, 13, 16, 19, 22, 25
3	7	1, 5, 9, 13, 17, 21, 25
4	5	3, 8, 13, 18, 23
5	5	1, 7, 13, 19, 25

3.5 U-Net-based reconstruction model with SE channel attention

The reconstruction model maps the heterogeneous active–passive observations to a normalized radar reflectivity field in the cross-track–vertical plane. All implementation tensors are ordered as batch, channel, cross-track, and vertical dimensions. Thus, the model input has shape $(N, 28, 25, 300)$, where N is the number of samples in a mini-batch, 28 is the number of input channels, 25 is the number of cross-track radar beams, and 300 is the number of vertical range bins in each beam. The two-dimensional U-Net-based encoder–decoder implements the mapping in Eq. (3) and produces a single-channel output with shape $(N, 1, 25, 300)$. The output therefore represents a complete normalized reflectivity field with the same cross-track and vertical dimensions as the target. Training and evaluation focus on the unobserved pixels because reflectivity at the retained beams is supplied directly by the radar measurements.

The encoder and decoder extract and combine precipitation structures at multiple spatial scales (Ronneberger et al., 2015). The three encoder stages (E1–E3) use 28, 50, and 100 feature channels, respectively, and the bottleneck (B4) uses 200 feature channels. Each stage contains two consecutive 3×3 convolutions, each followed by batch normalization and a rectified linear unit (ReLU), followed by an SE block. Downsampling between successive encoder stages progressively reduces the cross-track and vertical resolution. The three decoder stages (D3–D1) use 100, 50, and 28 feature channels, respectively. At each decoder stage, a transposed convolution upsamples the feature map, which is concatenated with the encoder feature map at the corresponding scale and processed by another double-convolution and SE block. These skip connections preserve spatial details from the encoder, while deeper features represent broader cross-track–vertical precipitation structures. The decoder restores the original 25×300 spatial domain, and a final 1×1 convolution maps the decoded features to the single-channel normalized reflectivity prediction. No additional activation function is applied after the output convolution, yielding a linear regression output. The prediction is clipped to $[-1, 1]$ only during evaluation before inverse normalization.

SE modules were inserted after every double-convolution block in the encoder, bottleneck, and decoder to recalibrate the latent feature channels using scene-dependent information (Hu et al., 2018). This operation is motivated by the heterogeneous roles of the sparse radar reflectivity and passive microwave channels in the input. For a feature tensor $\mathbf{F} \in \mathbb{R}^{C \times W_f \times H_f}$, global

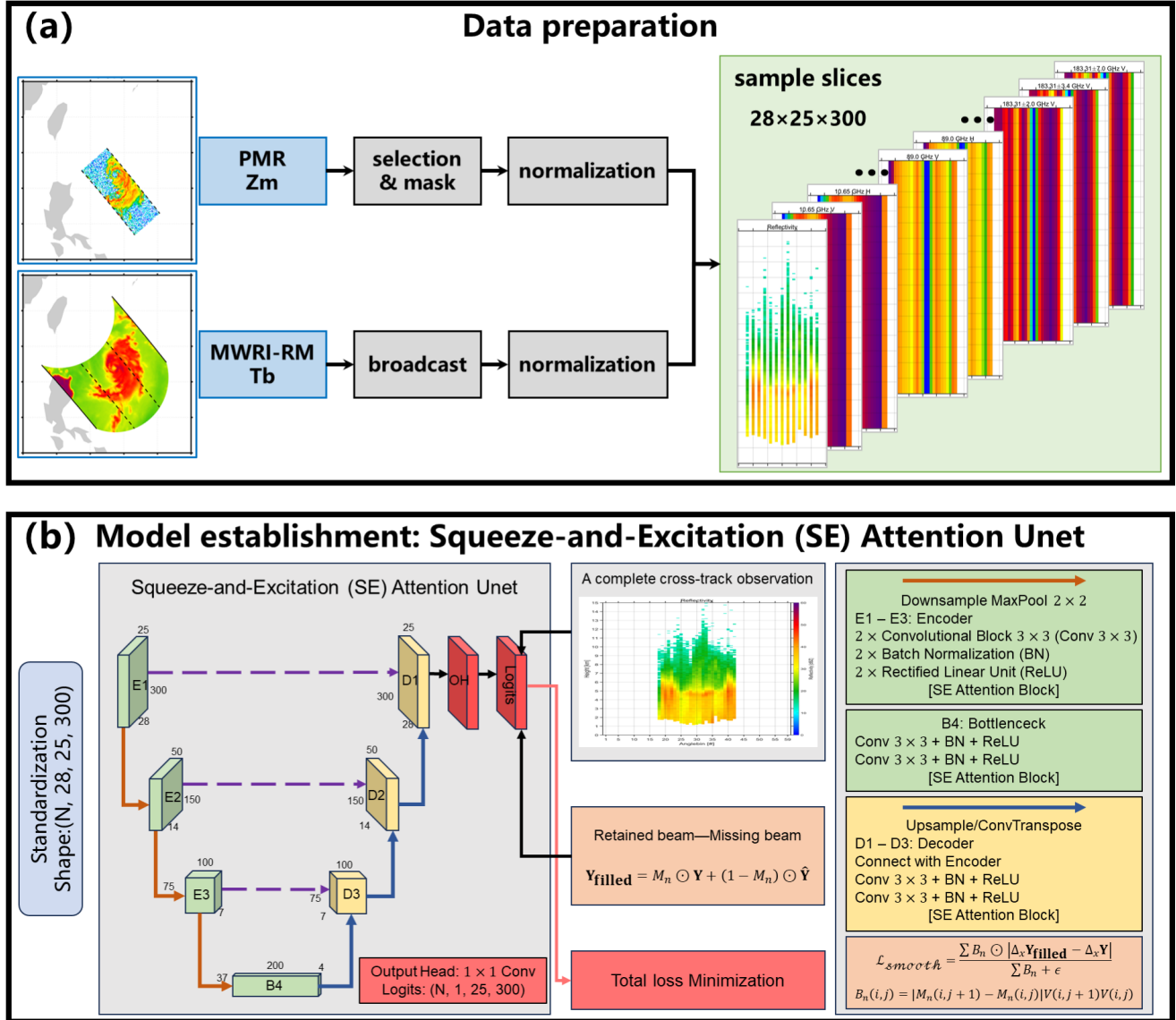


Figure 3. (a) Data preparation for the active–passive reconstruction samples. The model input comprises PMR reflectivity in the first channel, a binary beam-availability mask in the second channel (1 for retained beams and 0 for unobserved positions), and 26 vertically replicated MWRI-RM brightness-temperature channels, giving $28 \times 25 \times 300$ elements in channel–cross-track–vertical order. (b) SE-U-Net reconstruction framework. Multiscale features and SE channel attention combine the three input components to predict reflectivity at unobserved positions. Retained radar beams are then inserted to form the filled field used for the boundary-weighted loss and qualitative evaluation. Tensor definitions and loss equations are given in Eqs. (2)–(17).



average pooling first compresses each feature channel into a scalar descriptor:

$$s_c = \frac{1}{W_f H_f} \sum_{i=1}^{W_f} \sum_{j=1}^{H_f} F_c(i, j), \quad (8)$$

where c is the feature-channel index and $\mathbf{s} = [s_1, \dots, s_C]^T$ is the resulting channel descriptor. Two fully connected layers transform this descriptor into a set of channel-wise weights:

$$\mathbf{a} = \sigma(\mathbf{W}_2 \delta(\mathbf{W}_1 \mathbf{s})), \quad (9)$$

where $\mathbf{W}_1$ and $\mathbf{W}_2$ are learned weight matrices, δ denotes the ReLU activation within the SE module, and σ denotes the sigmoid function. The reduction ratio was set to $r = 16$, and the hidden excitation dimension was defined as $C_r = \max(1, \lfloor C/r \rfloor)$, accordingly, $\mathbf{W}_1 \in \mathbb{R}^{C_r \times C}$ and $\mathbf{W}_2 \in \mathbb{R}^{C \times C_r}$. The sigmoid constrains each component of $\mathbf{a}$ to the interval $(0, 1)$. The original feature tensor is then recalibrated channel by channel:

$$\tilde{F}_c(i, j) = a_c F_c(i, j), \quad (10)$$

where the same scene-dependent coefficient a_c is applied at all spatial positions of feature channel c . The recalibrated tensor $\tilde{\mathbf{F}}$ is passed to the next network operation. Importantly, these SE coefficients weight latent network features rather than the 28 model input channels directly, the input-channel sensitivity analysis described in the evaluation subsection is a separate inference-time diagnostic. The resulting SE-U-Net thus combines multiscale spatial encoding with adaptive feature recalibration while preserving spatial information through the encoder–decoder skip connections.

3.6 Loss function and training strategy

The reconstruction task focuses on estimating the masked, unobserved radar positions, while the retained beams are assumed to be directly available from radar measurements. Therefore, the main reconstruction loss was computed only over the masked regions. The valid gap mask is defined as

$$G_n = (1 - M_n) \odot V. \quad (11)$$

The gap-region mean absolute error is given by

$$\mathcal{L}_{\text{gap}} = \frac{\sum |\hat{\mathbf{Y}} - \mathbf{Y}| \odot G_n}{\sum G_n + \epsilon}, \quad (12)$$

where ϵ is a small constant used to avoid division by zero. To emphasize precipitating echoes within the unsampled regions, an additional rain-region loss was computed over pixels satisfying the precipitation mask, with the precipitation thresholds set to the PMR detection sensitivities reported by Liu et al. (2025):

$$\mathcal{L}_{\text{rain}} = \frac{\sum |\hat{\mathbf{Y}} - \mathbf{Y}| \odot G_n \odot R^{(b)}}{\sum G_n \odot R^{(b)} + \epsilon}. \quad (13)$$



In addition to the gap and precipitation-focused losses, a boundary-weighted term was introduced to emphasize reconstruction near the transitions between retained and unobserved radar beams. A filled field was constructed as

$$\mathbf{Y}_{\text{filled}} = M_n \odot \mathbf{Y} + (1 - M_n) \odot \hat{\mathbf{Y}}, \quad (14)$$

255 and the boundary loss was defined as

$$\mathcal{L}_{\text{smooth}} = \frac{\sum B_n \odot |\Delta_x \mathbf{Y}_{\text{filled}} - \Delta_x \mathbf{Y}|}{\sum B_n + \epsilon}, \quad (15)$$

where Δ_x denotes the first-order finite difference along the cross-track dimension, and

$$B_n(i, j) = |M_n(i + 1, j) - M_n(i, j)| \quad (16)$$

identifies transitions between retained and unobserved beams. Because the observed endpoint is taken directly from the target,

260 $\mathcal{L}_{\text{smooth}}$ effectively imposes an additional reconstruction penalty on gap pixels adjacent to retained beams.

The final training loss is

$$\mathcal{L} = \mathcal{L}_{\text{gap}} + \lambda_{\text{rain}} \mathcal{L}_{\text{rain}} + \lambda_{\text{smooth}} \mathcal{L}_{\text{smooth}}. \quad (17)$$

In the experiments reported here, $\lambda_{\text{rain}} = 1.0$ and $\lambda_{\text{smooth}} = 0.2$.

Models were trained independently for each radar band and beam-spacing configuration. The AdamW optimizer was used
265 with an initial learning rate of 10^{-4} . The validation subset was used to monitor model performance and select the checkpoint with the lowest validation loss, this checkpoint was then evaluated on the independent two-orbit test set.

3.7 Evaluation metrics and channel-importance analysis

The main evaluation metrics include mean absolute error (MAE), root-mean-square error (RMSE), mean bias, and standard deviation (SD) of the reconstruction error:

$$270 \quad e = \hat{Z} - Z, \quad (18)$$

$$\text{MAE} = \frac{1}{N_{\text{pix}}} \sum |e|, \quad \text{RMSE} = \sqrt{\frac{1}{N_{\text{pix}}} \sum e^2}, \quad (19)$$

$$\text{Bias} = \frac{1}{N_{\text{pix}}} \sum e, \quad \text{SD} = \sqrt{\frac{1}{N_{\text{pix}}} \sum (e - \text{Bias})^2}, \quad (20)$$

275 where N_{pix} is the number of valid pixels at masked radar positions. The same metrics were calculated as a function of physical height using the 50 m PMR vertical sampling interval, allowing the vertical distribution of reconstruction error to be examined.



To diagnose model sensitivity to the passive microwave information, a zero-out ablation was applied separately to each of the 26 standardized MWRI-RM brightness-temperature channels during inference. Setting T'_c to zero replaces that channel by its training-set mean in standardized space. The increase in gap-region RMSE relative to the unmodified inference was defined as the channel-sensitivity score:

$$S_c = \text{RMSE}_{c=0} - \text{RMSE}_{\text{base}}. \quad (21)$$

This diagnostic was applied to the trained Ku- and Ka-band models under each beam-spacing configuration. Because the MWRI-RM channels are mutually correlated, S_c is interpreted as model sensitivity to removal of one channel rather than as an independent or causal measure of that channel's physical contribution.

285 4 Results

4.1 Ku-band reflectivity reconstruction

4.1.1 Statistical evaluation

Figure 4 summarizes the statistical performance of the Ku-band reflectivity reconstruction under the five beam-spacing configurations. All metrics were computed exclusively over valid pixels within the masked inter-beam regions. Reconstruction accuracy generally degraded with increasing beam spacing, reflecting the progressive reduction in direct radar constraints available to the model. For $n = 1$, the MAE and RMSE aggregated over the clutter-free portion of the reflectivity profiles remained below 1.5 and 2.0 dB, respectively. It should be noted that the $n = 3$ configuration exhibited elevated errors above approximately 12 km, likely reflecting the reduced number of valid samples available at these altitudes and the resulting greater statistical variability (Appendix Fig. A1). When the beam spacing increased to $n = 5$, the overall MAE and RMSE increased to approximately 2.0 and 3.0 dB, respectively. The SD similarly increased from approximately 2.0 to 3.0 dB, indicating greater reconstruction uncertainty under increasingly sparse radar sampling.

The height-dependent statistics further demonstrate that the reconstruction errors were vertically heterogeneous. The MAE, RMSE, and SD increased toward the lower portion of the profiles, particularly for the sparser $n = 4$ and $n = 5$ configurations. The enhanced low-level errors are likely associated with the stronger horizontal variability of precipitation and residual uncertainty near the clutter-free-bottom boundary. A secondary increase in the reconstruction errors was also evident around 4–5 km, which is likely related to the enhanced reflectivity variability associated with the melting layer. Above approximately 5 km, the errors were generally smaller, indicating more consistent reconstruction of the mid- and upper-level precipitation structures. These features are also reflected in the vertical distribution of the observed reflectivity variability, with enhanced standard deviation in the lower troposphere and around the melting-layer altitude (Appendix Fig. A3). The broadly similar shapes of the error profiles across the five configurations suggest that increasing beam spacing primarily amplified the error magnitude without fundamentally altering its vertical distribution.

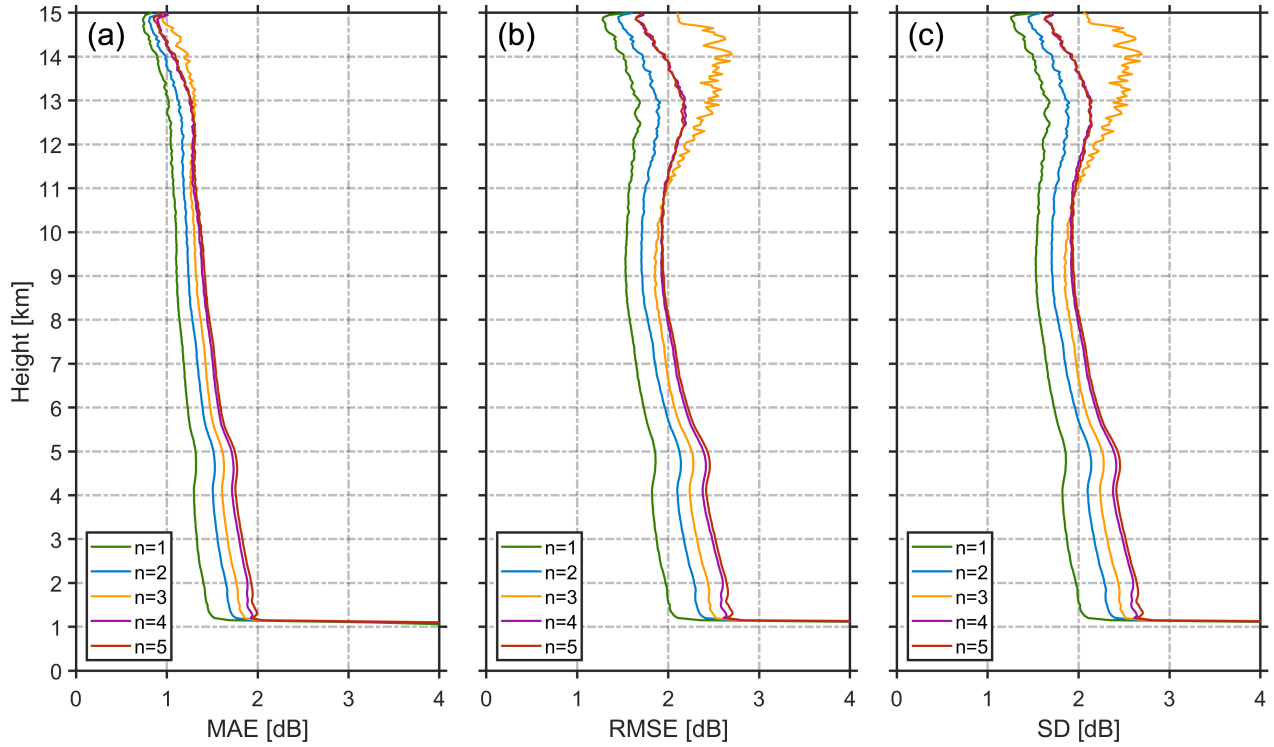


Figure 4. Statistical evaluation of the reconstructed PMR Ku-band reflectivity under the five beam-spacing configurations ($n = 1-5$). The panels show the vertical profiles of (a) mean absolute error (MAE), (b) root-mean-square error (RMSE), and (c) standard deviation (SD), calculated over valid pixels within the masked inter-beam regions. A larger value of n denotes a wider separation between adjacent retained radar beams.

4.1.2 Channel-importance analysis

Figure 5 presents the channel-ablation results for the Ku-band reconstruction, and Table 3 lists the six most influential input channels under each beam-spacing configuration. Zeroing the sparse Ku-band reflectivity channel produced the largest increase in gap-region RMSE for all five configurations, indicating that the retained radar observations provided the principal physical constraints on the reconstructed fields. Several MWRI-RM brightness-temperature channels also produced appreciable RMSE increases when zeroed, demonstrating that passive microwave observations supplied complementary information within regions lacking direct radar measurements.

Among the passive microwave inputs, the 36.5 GHz channels exhibited the most consistent contribution. The vertically and horizontally polarized 36.5 GHz channels occupied the second and third positions under all five beam-spacing configurations. The 18.7 GHz channels also appeared among the six most influential inputs for every configuration. The persistent importance of these two frequency groups is physically consistent with their sensitivity to rain-induced microwave emission over ocean. Against the comparatively cold, low-emissivity ocean background, absorption and emission by liquid hydrometeors increase



the observed brightness temperature, while dual-polarization measurements provide additional information for separating pre-
320 cipitation signals from variations in surface emissivity (Kummerow et al., 2001; Petty and Li, 2013).

The remaining influential channels varied more substantially among the five configurations. The 89.0 GHz channels appeared
among the six leading inputs for $n = 1$, $n = 4$, and $n = 5$, whereas the 23.8 GHz and 183.31 ± 7.0 GHz channels appeared
only for $n = 2$ and $n = 3$, respectively. The 89.0 GHz channels provide complementary sensitivity to the 3D organization
of precipitation because their brightness temperatures are affected by scattering from frozen hydrometeors, in addition to
325 contributions from liquid precipitation and the oceanic background (Cecil and Chronis, 2018; Guilloteau et al., 2018). The
intermittent occurrence of the 23.8 and 183.31 GHz channels suggests that information related to atmospheric water vapor and
high-frequency hydrometeor scattering was used under particular sampling configurations rather than constituting a persistent
constraint.

Overall, the Ku-band reconstruction relied on a stable core of 18.7 and 36.5 GHz passive microwave information, supple-
330 mented by a more configuration-dependent combination of 23.8, 89.0, and 183.31 GHz observations. Because the ablation
analysis quantifies the marginal response to zeroing one channel while retaining all other inputs, the resulting rankings may
also reflect redundancy and correlation among the MWRI-RM channels. They should therefore be interpreted as measures of
model sensitivity to the prescribed channel perturbation rather than as unique or independent measures of physical information
content.

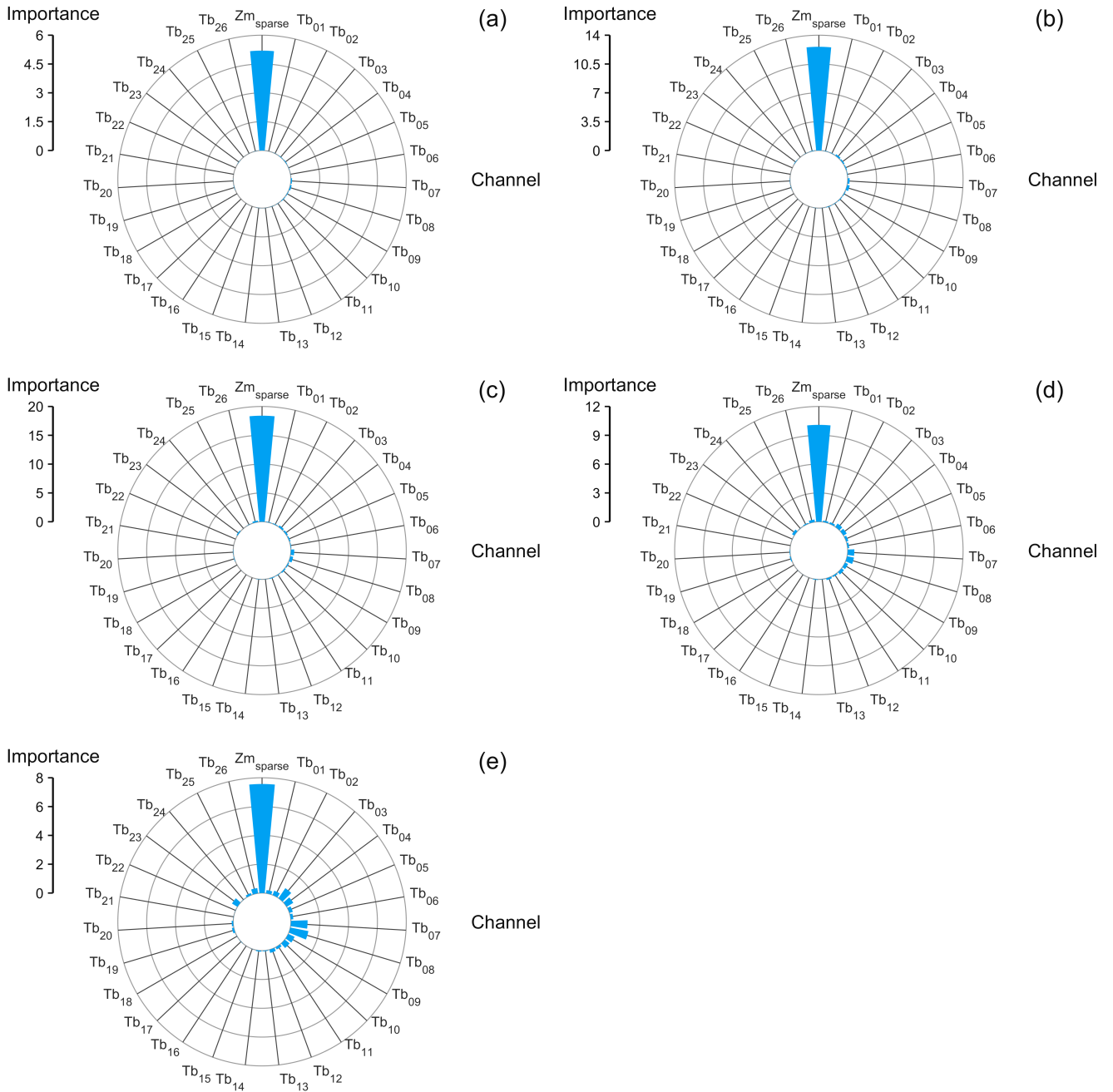


Figure 5. Input-channel importance for the PMR Ku-band reflectivity reconstruction under the five beam-spacing configurations. Channel importance is defined as the increase in gap-region RMSE when an individual normalized input channel is set to zero during inference. The beam-mask channel is excluded because it represents the prescribed observation geometry rather than an independent physical measurement. Positive values indicate that zeroing the corresponding channel degrades reconstruction performance.



Table 3. Six most influential input channels for the PMR Ku-band reflectivity reconstruction under the five beam-spacing configurations. The channels are ranked according to the increase in gap-region RMSE obtained after zeroing each normalized input channel.

Rank	$n = 1$	$n = 2$	$n = 3$	$n = 4$	$n = 5$
1	Zm_{sparse}	Zm_{sparse}	Zm_{sparse}	Zm_{sparse}	Zm_{sparse}
2	$Tb_{08}, 36.5 \text{ GHz, H}$	$Tb_{08}, 36.5 \text{ GHz, H}$	$Tb_{07}, 36.5 \text{ GHz, V}$	$Tb_{08}, 36.5 \text{ GHz, H}$	$Tb_{08}, 36.5 \text{ GHz, H}$
3	$Tb_{07}, 36.5 \text{ GHz, V}$	$Tb_{07}, 36.5 \text{ GHz, V}$	$Tb_{08}, 36.5 \text{ GHz, H}$	$Tb_{07}, 36.5 \text{ GHz, V}$	$Tb_{07}, 36.5 \text{ GHz, V}$
4	$Tb_{04}, 18.7 \text{ GHz, H}$	$Tb_{03}, 18.7 \text{ GHz, V}$	$Tb_{03}, 18.7 \text{ GHz, V}$	$Tb_{03}, 18.7 \text{ GHz, V}$	$Tb_{03}, 18.7 \text{ GHz, V}$
5	$Tb_{10}, 89.0 \text{ GHz, H}$	$Tb_{04}, 18.7 \text{ GHz, H}$	$Tb_{26}, 183.31 \pm 7.0 \text{ GHz, V}$	$Tb_{04}, 18.7 \text{ GHz, H}$	$Tb_{04}, 18.7 \text{ GHz, H}$
6	$Tb_{09}, 89.0 \text{ GHz, V}$	$Tb_{05}, 23.8 \text{ GHz, V}$	$Tb_{04}, 18.7 \text{ GHz, H}$	$Tb_{09}, 89.0 \text{ GHz, V}$	$Tb_{09}, 89.0 \text{ GHz, V}$

335 4.2 Ka-band reflectivity reconstruction

4.2.1 Statistical evaluation

Figure 6 summarizes the statistical performance of the Ka-band reflectivity reconstruction under the five beam-spacing configurations. Although the reconstruction errors generally increased with increasing beam spacing, the MAE, RMSE, and SD below approximately 11 km remained, overall, below about 1.5, 2.5, and 2.5 dB, respectively, across the $n = 1$ –5 configurations. These errors were generally smaller than those obtained for the Ku-band reconstruction, indicating better reconstruction performance for the Ka-band observations over most of the lower and middle troposphere.

A notable distinction from the Ku-band results was the vertical distribution of the Ka-band reconstruction errors. The error profiles exhibited a broad minimum between approximately 3 and 11 km, with larger errors near the lower part of the profiles. The enhanced low-level errors are likely associated with the stronger horizontal variability of precipitation and residual uncertainty near the clutter-free-bottom boundary. In contrast to the Ku-band results, the increase in reconstruction error around 4–5 km was less pronounced for the Ka band. This difference is likely related to the stronger attenuation of the Ka-band radar signal (Zeng et al., 2026), which weakens the reflectivity enhancement associated with the melting layer and reduces its contrast relative to the surrounding precipitation. These vertical characteristics are consistent with the height-dependent variability of the observed reflectivity, as indicated by the Fig. A3 in Appendix.

Above approximately 11 km, the Ka-band reconstruction errors increased again. The primary explanation is likely the comparatively weak and narrowly distributed upper-tropospheric Ka-band reflectivities in the present dataset (Appendix Fig. A2). Because the same 0–60 dBZ normalization range was applied to both radar frequencies, these relatively weak Ka-band echoes occupied only a limited portion of the normalized target range, making their spatial variability less prominent during training. A secondary factor is the sharp decrease in the number of valid gap pixels above 10 km (Appendix Fig. A1), which makes the estimated MAE, RMSE, and SD more sensitive to a relatively small number of large reconstruction errors. The enhanced upper-level errors therefore likely reflect the combined effects of weak Ka-band reflectivity signals and reduced sample support.

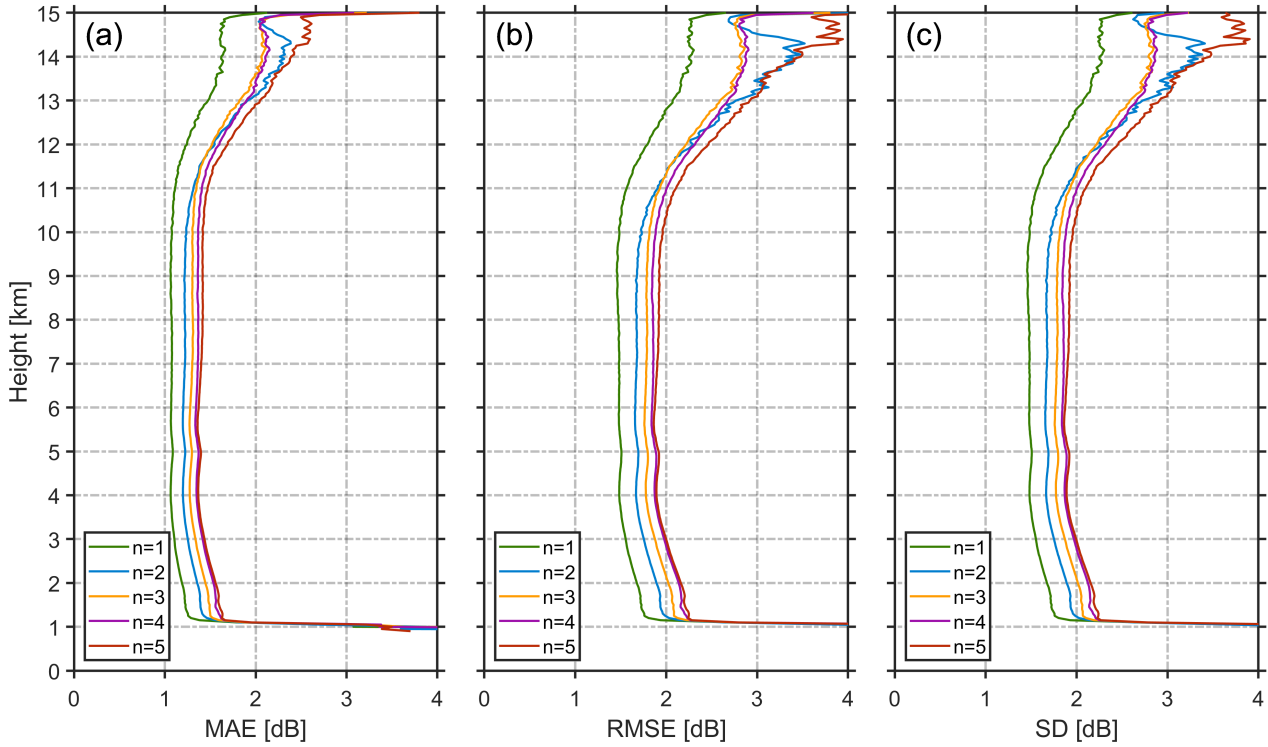


Figure 6. Same as Fig. 4 but for the Ka-band reflectivity reconstruction.

4.2.2 Channel-importance analysis

Figure 7 presents the channel-ablation results for the Ka-band reconstruction, and Table 4 lists the six most influential input channels under each beam-spacing configuration. As in the Ku-band experiment, zeroing the sparse radar reflectivity channel produced the largest increase in gap-region RMSE for all five configurations, confirming that the retained Ka-band radar beams provided the primary physical constraints on the reconstructed fields.

Among the passive microwave inputs, the 36.5 GHz channels again exhibited the most consistent contribution. The horizontally polarized 36.5 GHz channel ranked second for $n = 1-4$, whereas the vertically polarized channel ranked second for $n = 5$. Both polarizations remained among the four most influential channels under every configuration. This persistent importance is physically consistent with the sensitivity of the 36.5 GHz window channels to rain-induced microwave emission over ocean, particularly for light and moderate liquid precipitation (Petty and Li, 2013).

In contrast to the Ku-band results, the identities and rankings of the secondary passive microwave channels varied more substantially with beam spacing. The 18.7 GHz channels appeared among the six leading inputs for $n = 2-5$, whereas the 10.65 GHz channels appeared for $n = 1$ and $n = 4$. The 89.0 GHz channels were selected for $n = 1$ and $n = 5$. The lower-frequency window channels provide complementary information on liquid precipitation through rain-induced emission and



polarization contrast over the radiometrically cold ocean surface. The configuration-dependent occurrence of these channels suggests that the model adjusted its use of liquid-precipitation information as the density and spatial distribution of the retained Ka-band observations changed.

Higher-frequency passive microwave channels also contributed under several configurations. The 165.5 GHz channel appeared among the six most influential inputs for $n = 2-4$, whereas the 183.31 ± 7.0 GHz channel appeared for $n = 3$ and $n = 5$. Channels near 89 and 165.5 GHz are sensitive to scattering by frozen hydrometeors and therefore provide information related to ice-phase precipitation and the vertical development of precipitation systems (Guilloteau et al., 2018). The 183.31 ± 7.0 GHz channel lies in the wing of the water-vapor absorption band and combines vertically weighted humidity information with sensitivity to cloud ice and precipitation scattering (Yang et al., 2025).

Overall, the Ka-band reconstruction relied on a stable core of 36.5 GHz information, supplemented by a more configuration-dependent combination of lower- and higher-frequency passive microwave channels. Compared with the Ku-band experiment, the greater variability in the secondary channel rankings may partly reflect the stronger attenuation of Ka-band radar observations, which can reduce the stability of the direct radar constraints and increase the relative dependence on complementary passive microwave information. Redundancy and correlation among the MWRI-RM channels may also contribute to the variation in channel rankings. As in the Ku-band analysis, these rankings represent the marginal model response to zeroing individual channels.

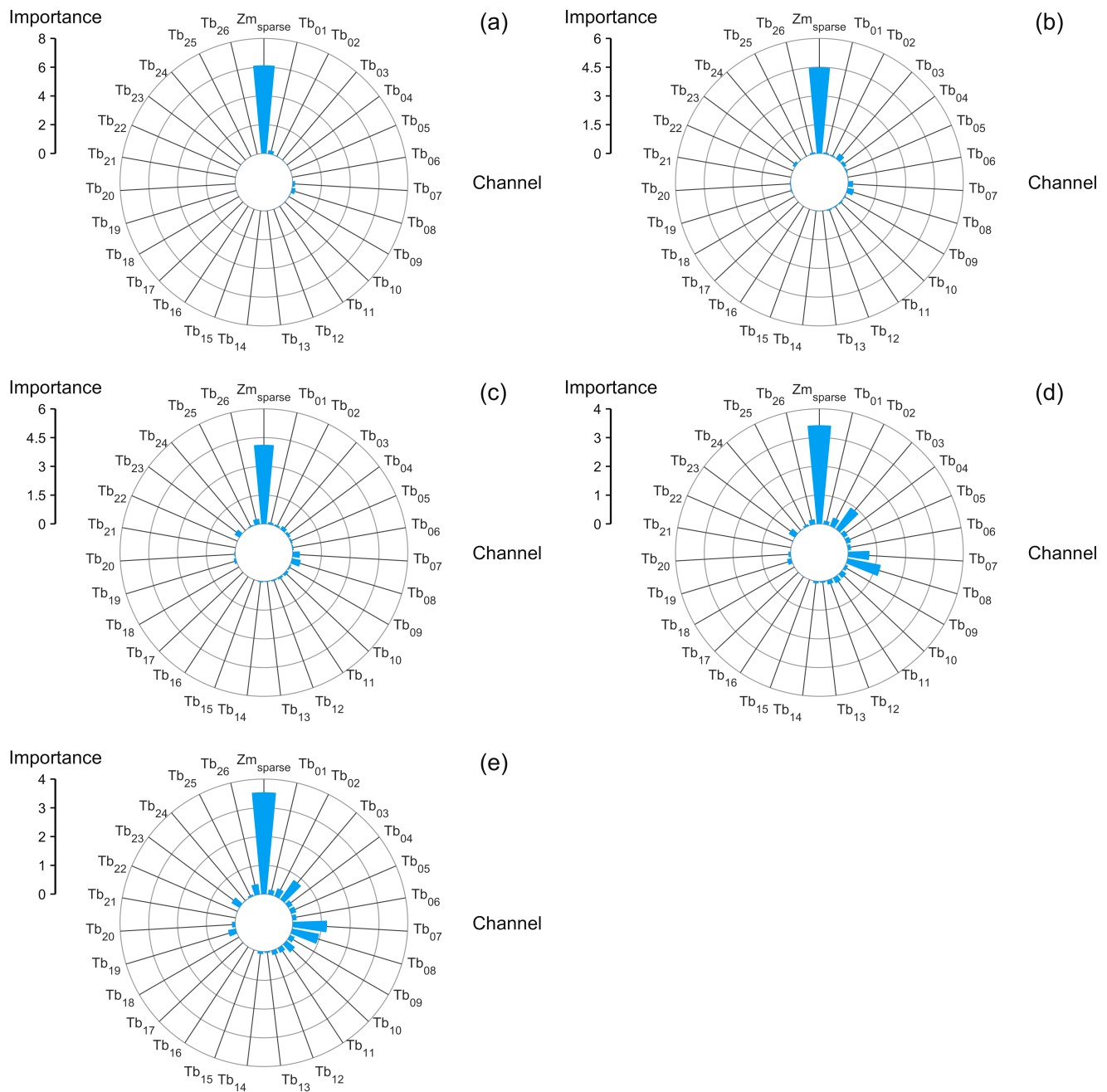


Figure 7. Same as Fig. 5 but for the Ka-band reflectivity reconstruction.



Table 4. Same as Tab. 3 but for the Ka-band reflectivity reconstruction.

Rank	$n = 1$	$n = 2$	$n = 3$	$n = 4$	$n = 5$
1	Zm_{sparse}	Zm_{sparse}	Zm_{sparse}	Zm_{sparse}	Zm_{sparse}
2	$Tb_{08}, 36.5 \text{ GHz, H}$	$Tb_{08}, 36.5 \text{ GHz, H}$	$Tb_{08}, 36.5 \text{ GHz, H}$	$Tb_{08}, 36.5 \text{ GHz, H}$	$Tb_{07}, 36.5 \text{ GHz, V}$
3	$Tb_{01}, 10.65 \text{ GHz, V}$	$Tb_{03}, 18.7 \text{ GHz, V}$	$Tb_{07}, 36.5 \text{ GHz, V}$	$Tb_{03}, 18.7 \text{ GHz, V}$	$Tb_{08}, 36.5 \text{ GHz, H}$
4	$Tb_{07}, 36.5 \text{ GHz, V}$	$Tb_{07}, 36.5 \text{ GHz, V}$	$Tb_{23}, 165.5 \pm 0.75 \text{ GHz, V}$	$Tb_{07}, 36.5 \text{ GHz, V}$	$Tb_{03}, 18.7 \text{ GHz, V}$
5	$Tb_{02}, 10.65 \text{ GHz, H}$	$Tb_{04}, 18.7 \text{ GHz, H}$	$Tb_{26}, 183.31 \pm 7.0 \text{ GHz, V}$	$Tb_{02}, 10.65 \text{ GHz, H}$	$Tb_{10}, 89.0 \text{ GHz, H}$
6	$Tb_{09}, 89.0 \text{ GHz, V}$	$Tb_{23}, 165.5 \pm 0.75 \text{ GHz, V}$	$Tb_{03}, 18.7 \text{ GHz, V}$	$Tb_{23}, 165.5 \pm 0.75 \text{ GHz, V}$	$Tb_{26}, 183.31 \pm 7.0 \text{ GHz, V}$

4.3 Case-study evaluation

To further evaluate the reconstruction performance, a case study was conducted for Super Typhoon Saola. Saola developed over the western North Pacific in late August 2023, underwent rapid intensification, and entered the South China Sea on 30 August while maintaining super typhoon intensity. On 31 August, the storm continued to move west-northwestward over the northern South China Sea as a mature tropical cyclone. During this period, FY-3G PMR observed the precipitation system, providing a representative case for evaluating the reconstruction of a highly organized tropical cyclone precipitation structure.

Figures 8 and 9 show the observed and reconstructed reflectivity structures for the Ku and Ka bands, respectively. Seven cross-track–vertical sections sampled during the PMR overpass are displayed together with the corresponding FY-4B satellite imagery to provide the spatial context of the storm. The original PMR observations reveal strong reflectivity cores near the eyewall and pronounced melting-layer signatures within the spiral rainbands. The reconstructed fields generally reproduce the locations, vertical extents, and cross-track organization of these features.

For the Ku band (Fig. 8), the reconstructed sections remain visually consistent with the original observations across the five beam-spacing configurations. At relatively small beam spacings, the reconstructed fields closely reproduce the observed cross-track–vertical reflectivity structure, including the locations and vertical development of the strong reflectivity cores and melting-layer features. As n increases, the unsampled regions become progressively wider, and the reconstruction relies more strongly on the passive microwave observations and the spatial context provided by the retained radar beams. Consequently, local differences become more evident for the sparsest configurations, although the principal precipitation structures remain well preserved. This behavior is consistent with the statistical results in Sect. 4.1, which show a gradual increase in reconstruction error with increasing beam spacing.

The Ka-band results (Fig. 9) exhibit a similar dependence on beam spacing but also reflect the distinct vertical characteristics of Ka-band reflectivity. The dominant precipitation structures are reproduced under all five configurations, while increasingly sparse radar sampling leads to greater local departures from the observations within the inter-beam regions. Compared with the Ku-band sections, the Ka-band echoes are generally weaker in the upper portions of the profiles, making weak high-altitude



410 features more difficult to reconstruct. Nevertheless, the reconstructed fields preserve the principal cross-track and vertical organization of the observed Ka-band precipitation system, consistent with the statistical results in Sect. 4.2.

Figures 10 and 11 provide a quantitative assessment of all valid inter-beam pixels sampled during the Saola overpass. For both radar frequencies, the highest sample densities are concentrated around the 1:1 line, indicating good overall agreement between the reconstructed and observed reflectivity values. As the beam spacing increases, the scatter distributions become
415 progressively broader, consistent with the reduced radar constraints and the increase in reconstruction errors found in the full-sample evaluation. For the Ka band, localized high-density departures from the 1:1 line further indicate the greater difficulty in reconstructing weak high-altitude echoes.

Taken together, the case study demonstrates that the proposed radar-constrained active–passive framework can accurately recover the dominant cross-track–vertical precipitation structures of a mature tropical cyclone under sparse radar sampling.

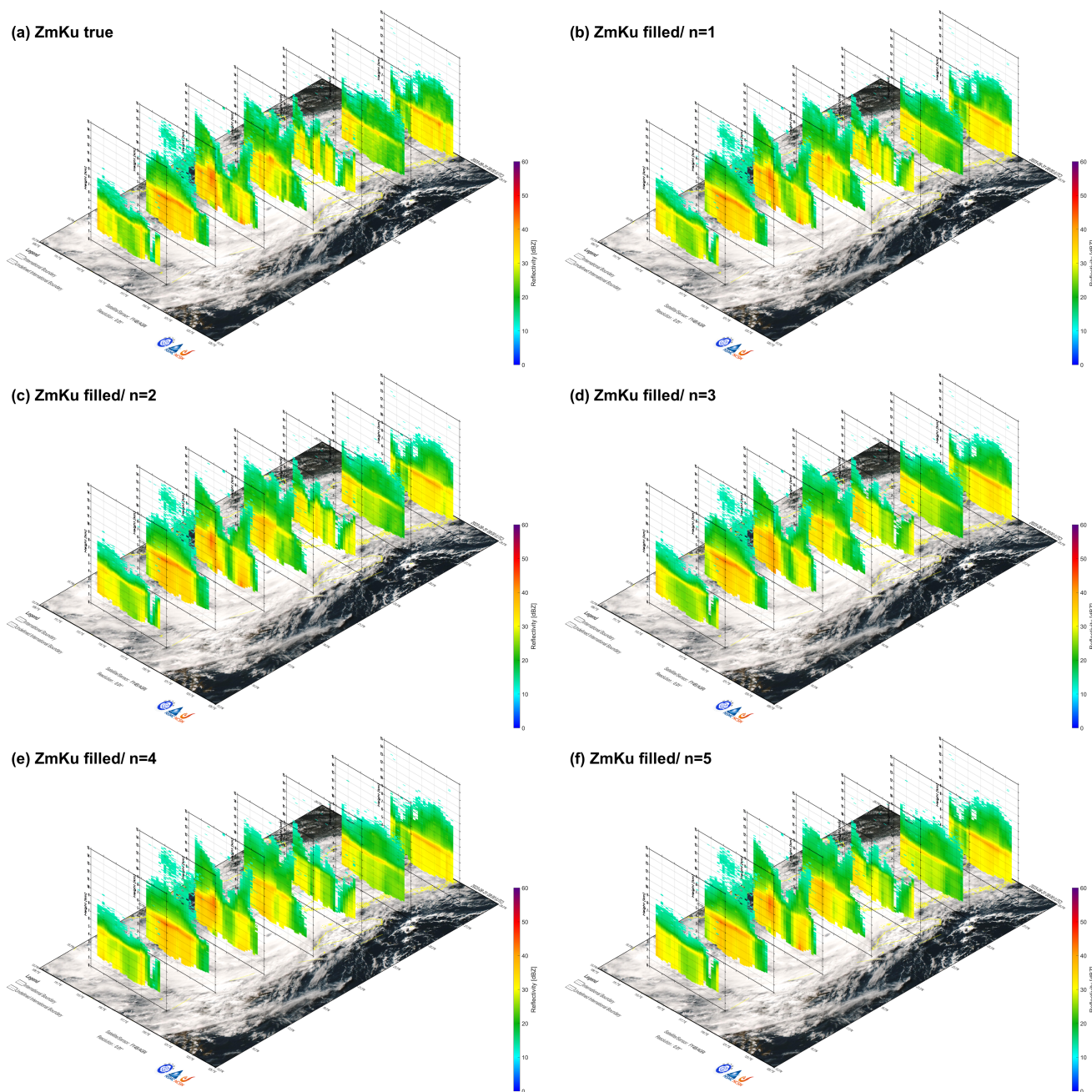


Figure 8. Observed and reconstructed Ku-band reflectivity structures of Super Typhoon Saola over the South China Sea on 31 August 2023. Seven selected cross-track–vertical PMR reflectivity sections (scans #2535, #2542, #2550, #2558, #2568, #2576 and #2584) are overlaid on the corresponding satellite imagery to illustrate the 3D precipitation structure. Panel (a) shows the original FY-3G PMR observations, while panels (b)–(f) show the reconstructed reflectivity fields for the five beam-spacing configurations ($n = 1$ – 5), respectively. The dimensions shown is not drawn to scale.

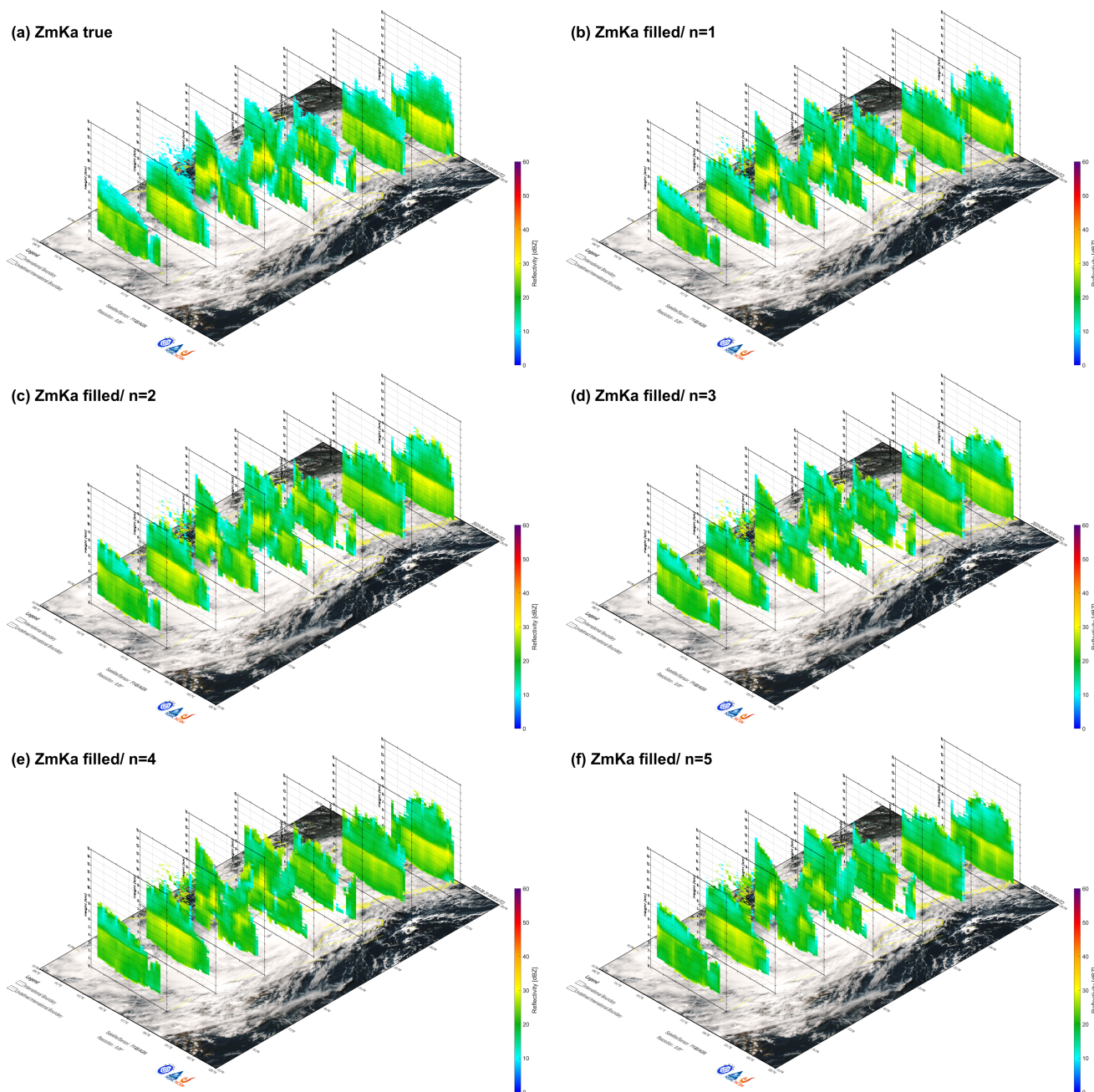


Figure 9. Same as Fig. 8, but for the PMR Ka-band reflectivity field.

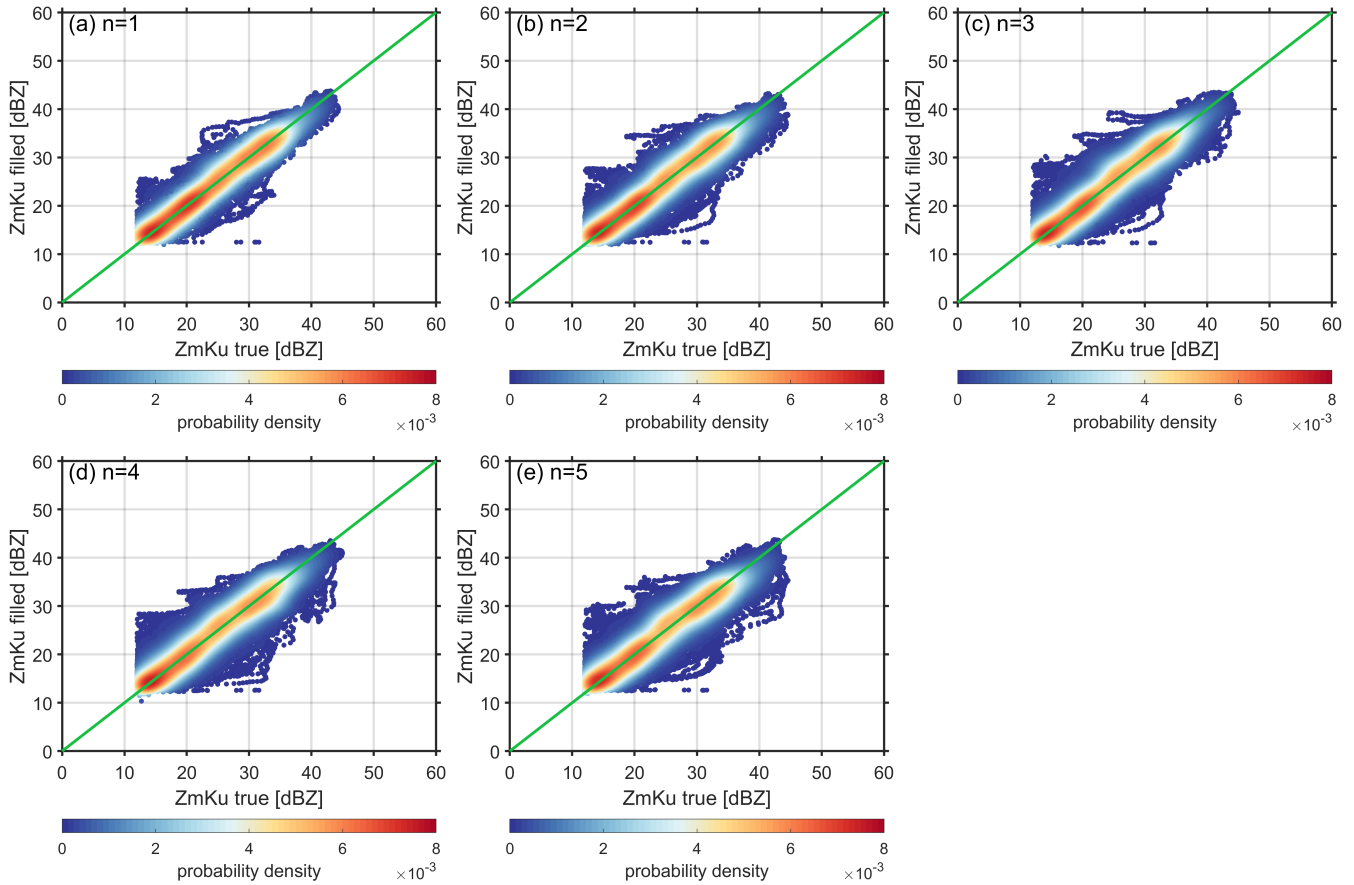


Figure 10. Scatter-density comparisons between the observed and reconstructed Ku-band reflectivity for the Super Typhoon Saola case on 31 August 2023. All valid pixels within the reconstructed inter-beam regions over the complete PMR overpass are included. The shading indicates the relative density of samples. The panels correspond to the five beam-spacing configurations ($n = 1-5$). The 1:1 line denotes perfect agreement between the observations and reconstructions.

420 5 Conclusions and discussion

This study introduced a discrete multi-beam spaceborne precipitation radar concept and developed a radar-constrained active-passive inpainting framework for reconstructing unobserved regions between adjacent radar beams. Using collocated FY-3G PMR and MWRI-RM observations, the framework was evaluated independently for the Ku- and Ka-band radars under five typical beam-spacing configurations. The proposed approach preserves the observed radar profiles as direct constraints while
 425 reconstructing only the inter-beam gaps. Across the examined configurations, in which one to five beams were skipped between adjacent retained beams, the overall MAE, RMSE, and SD remained below approximately 2.0, 3.0, and 3.0 dB, respectively, for the Ku band and 1.5, 2.5, and 2.5 dB for the Ka band. These reconstruction errors are of a comparable order of magnitude to the approximately 1–2 dB calibration uncertainty commonly associated with ground-based weather radars (Doviak and Zrnić,

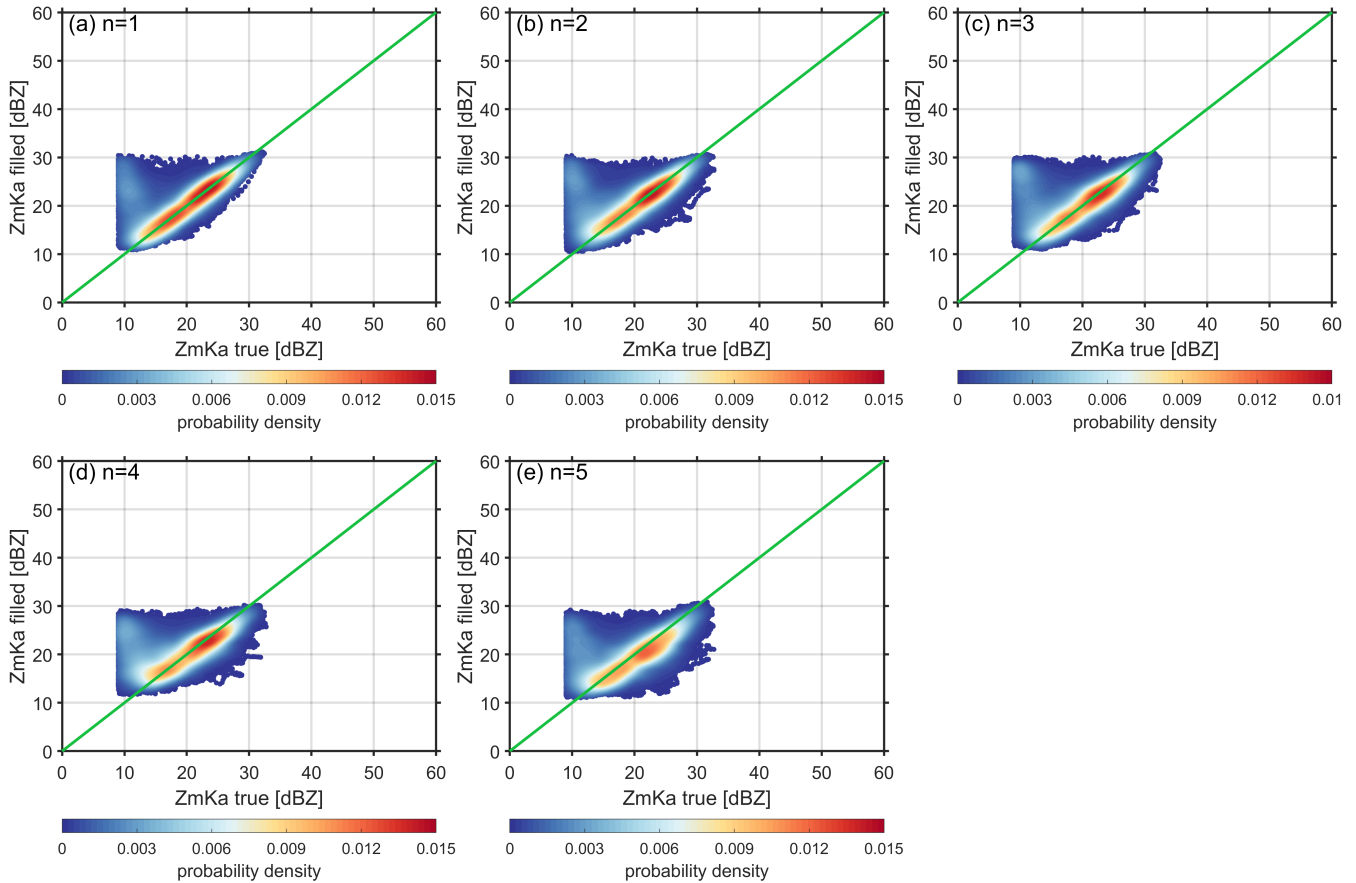


Figure 11. Same as Fig. 10, but for the PMR Ka-band reflectivity field.

2014), providing a practical reference for the accuracy achieved here. The results demonstrate that coherent 3D reflectivity
430 structures can be recovered with relatively high accuracy even under substantially reduced radar sampling.

The dependence of reconstruction accuracy on beam spacing provides an algorithm-informed basis for evaluating trade-offs among beam number, cross-track sampling extent, and payload or constellation cost. The present results, however, should not be interpreted as direct specifications for an optimal radar configuration because the sparse sampling was emulated by masking observations from the fully sampled PMR swath. Future system-level studies should therefore couple the reconstruction frame-
435 work with realistic radar simulations that account for antenna patterns, incidence angles, nonuniform beam filling, surface clutter, and other instrumental effects. Practical beam configurations should ultimately be determined by jointly considering reconstruction performance and engineering constraints.

The channel-importance analysis further demonstrates the complementary role of passive microwave observations in reconstructing unsampled radar structures. For both radar bands, the sparse reflectivity channel provided the dominant constraint,
440 while the 36.5 GHz channels consistently contributed substantial additional information. The Ku-band reconstruction also



showed relatively stable contributions from the 18.7 GHz channels, whereas the secondary passive-channel rankings varied more strongly for the Ka band. This greater variability may partly reflect the stronger attenuation of Ka-band radar observations and the resulting configuration-dependent reliance on complementary microwave information, together with redundancy and correlation among the MWRI-RM channels. Although these results may help identify potentially useful spectral channels
445 for coordinated active–passive payloads, the inferred importance remains model- and dataset-dependent. Future studies should therefore complement single-channel zero-out tests with grouped spectral ablation and retraining using reduced channel subsets before translating such sensitivities into payload-design recommendations.

The present study focuses primarily on interpolation between retained radar beams. Reconstruction beyond the outermost beams is more challenging because it becomes an extrapolation problem with weaker direct radar constraints. Future work
450 could extend the framework toward wide-swath reconstruction by combining sparse radar profiles with passive microwave observations over a broader domain. Polar-orbiting microwave imagers and sounders provide all-weather information on precipitation and hydrometeors, while geostationary visible and infrared observations provide complementary information on cloud evolution and horizontal organization (Hilburn et al., 2021; Xue et al., 2026). Future geostationary microwave observations may further enhance such reconstruction through frequent all-sky measurements from window and sounding channels
455 (Liu et al., 2026). Integrating these complementary observations offers a promising pathway toward wider and more temporally continuous 3D precipitation products.

The proposed approach may also be applicable to other spaceborne radar missions with sparse or irregular sampling geometries. For example, WIVERN (Wind Velocity Radar Nephoscope)-like observing concepts employ wide-swath radar sampling that requires the reconstruction of geophysical fields between discrete observations (Illingworth et al., 2018; Battaglia et al.,
460 2026). The radar-constrained active–passive strategy developed here therefore provides a potential basis for learned or hybrid reconstruction methods for such missions, although extension to irregular 3D Doppler observations would require substantial adaptation.

Several limitations remain. First, the sparse-beam geometry was simulated from fully sampled PMR observations rather than from a dedicated instrument simulator. Second, the dataset was restricted to oceanic precipitation with precipitation detected
465 across all 25 central beams and therefore does not fully represent land, weak, or isolated precipitation. Third, MWRI-RM brightness temperatures provide primarily column-integrated constraints and are subject to footprint and collocation differences relative to the radar observations. Finally, the current model operates on individual cross-track–vertical sections without explicitly exploiting along-track or temporal context. Future evaluation should therefore include a wider range of precipitation regimes and surface types, additional independent storm cases, and realistic simulations of candidate radar configurations.

470 *Code and data availability.* The code used for data preprocessing and model training can be provided upon request to the authors. FY-3G PMR and MWRI-RM data are publicly available at <https://satellite.nsmc.org.cn/DataPortal/en/home/index.html>.

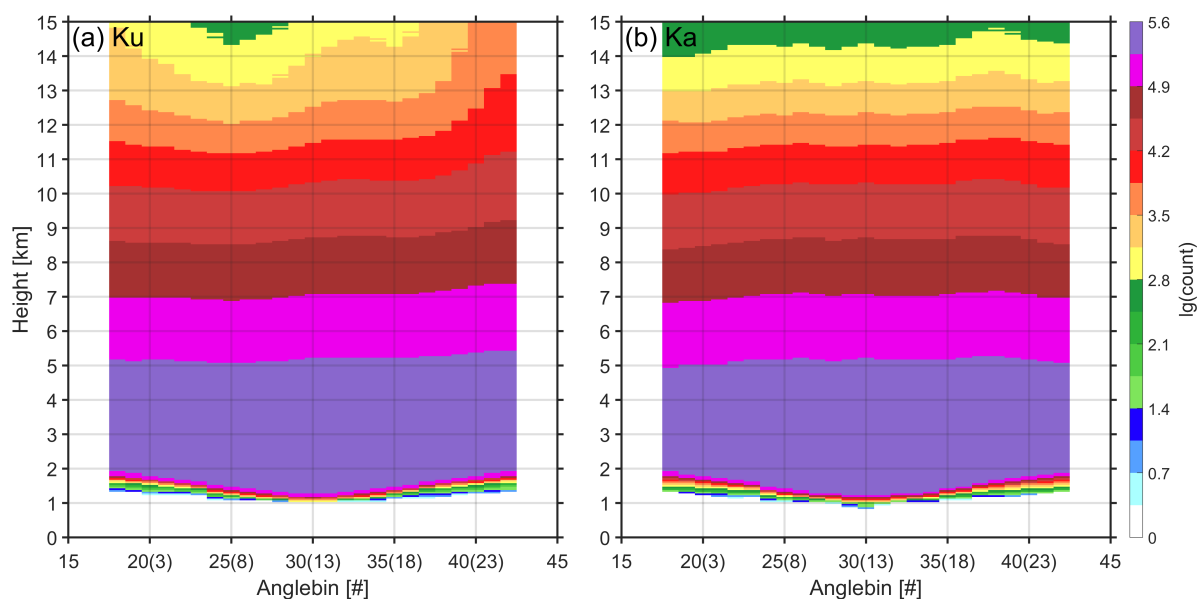


Figure A1. Vertical and cross-track distributions of valid PMR reflectivity observations for the (a) Ku- and (b) Ka-band. The x-axis tick labels denote the cross-track beam indices, ranging from 1 to 59 for the FY-3G PMR and from 1 to 25 for the proposed MPR configuration.

Appendix A: Sample Statistics

Author contributions. JS and HL conceived the idea and provided overall supervision. BL and YZ contributed to methodology development and algorithm implementation, conducted the analysis, and drafted the manuscript and figures. All authors reviewed and edited the manuscript, and provided critical feedback.

Competing interests. At least one of the (co-)authors is a member of the editorial board of Atmospheric Measurement Techniques. The authors have no other competing interests to declare.

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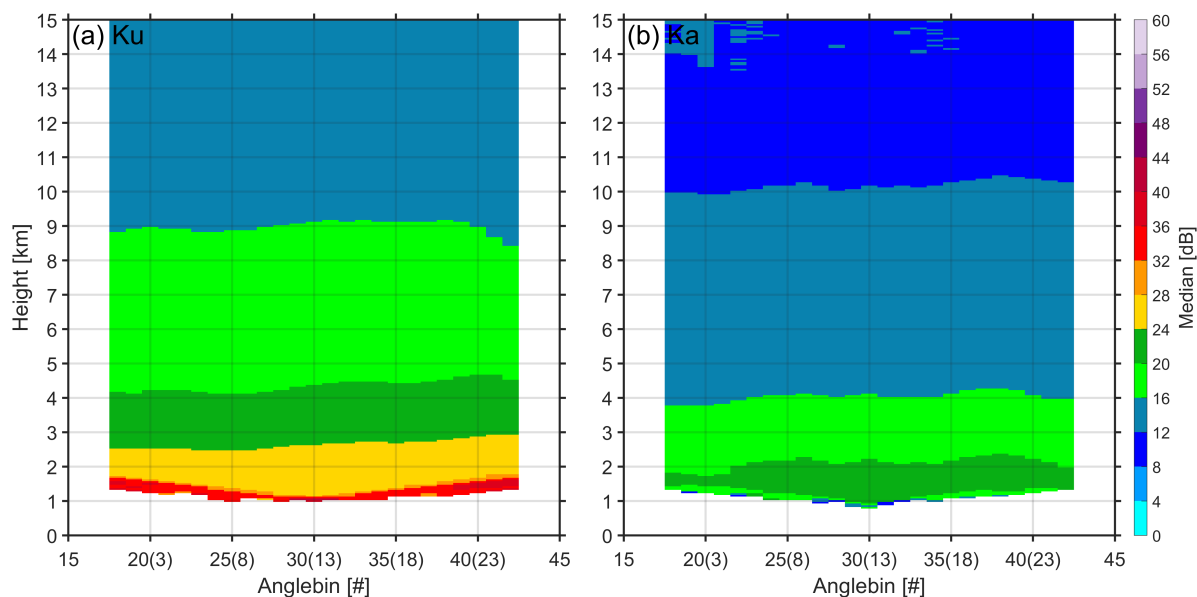


Figure A2. Vertical and cross-track distributions of (a) Ku- and (b) Ka-band PMR reflectivity median. The x-axis tick labels denote the cross-track beam indices, ranging from 1 to 59 for the FY-3G PMR and from 1 to 25 for the proposed MPR configuration.

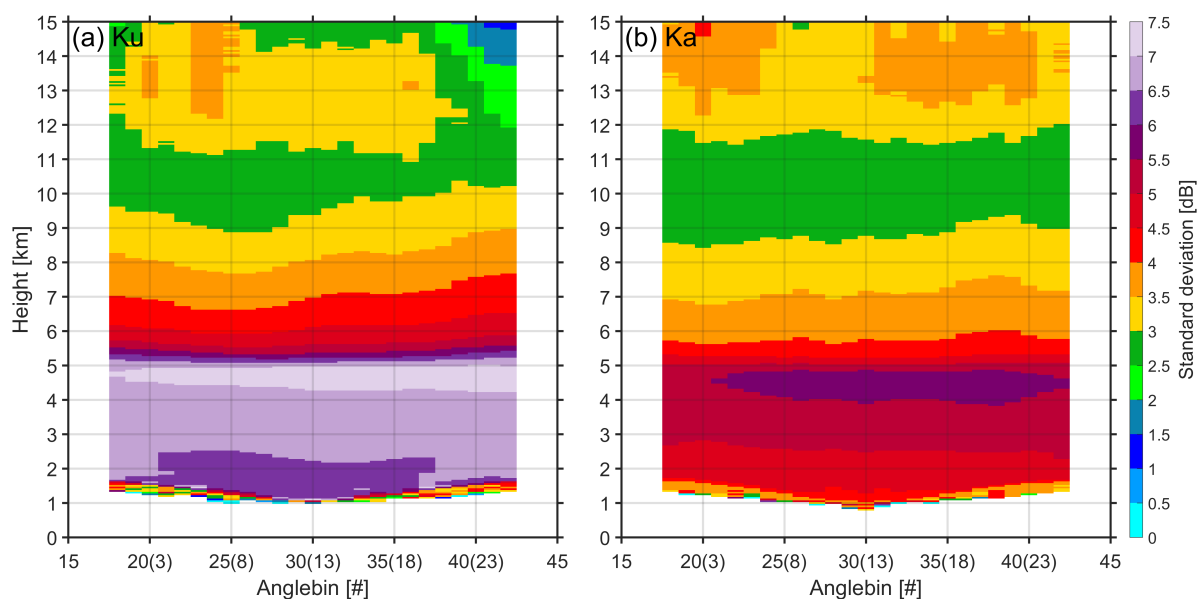


Figure A3. Vertical and cross-track distributions of (a) Ku- and (b) Ka-band PMR reflectivity standard deviation. The x-axis tick labels denote the cross-track beam indices, ranging from 1 to 59 for the FY-3G PMR and from 1 to 25 for the proposed MPR configuration.



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