

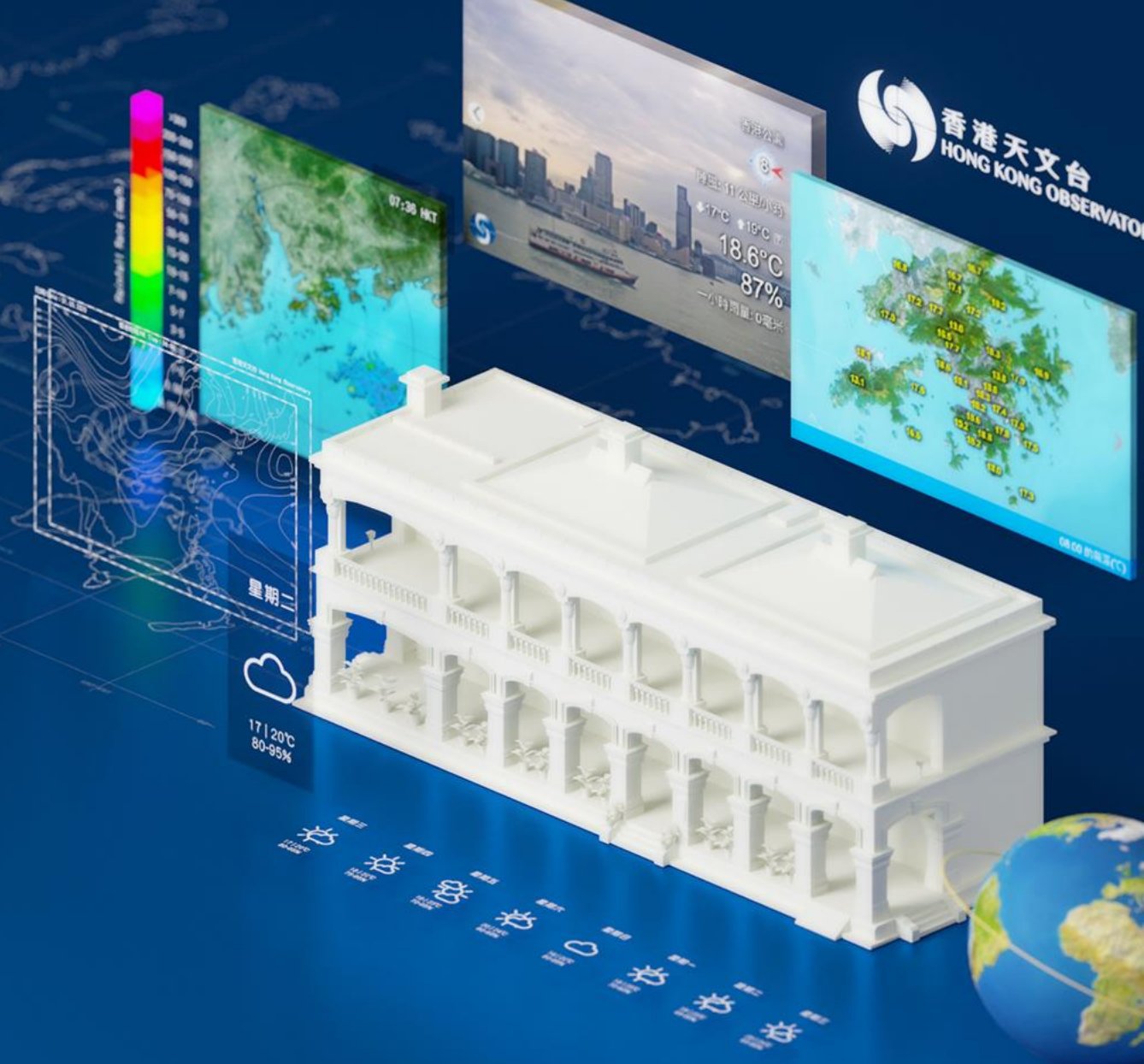
RADAR-BASED NOWCASTING TECHNIQUES (WITH PRACTICALS)

WMO Severe Weather Forecasting Programme (SWFP)
Regional Sub-programme for Southeast Asia (SWFP-SeA)
Training Desk and Study Visit for Cambodia
(Ha Noi, 19 - 23 May 2025)

Wai-Kin Wong

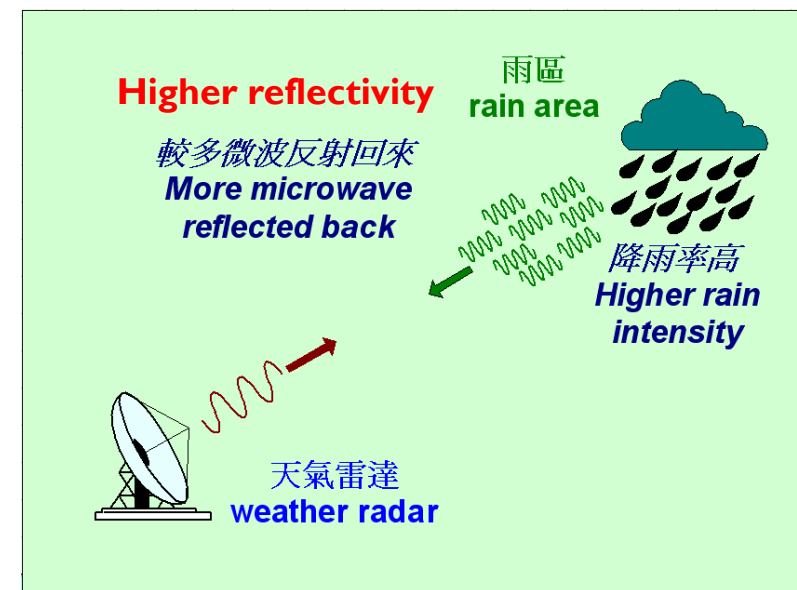
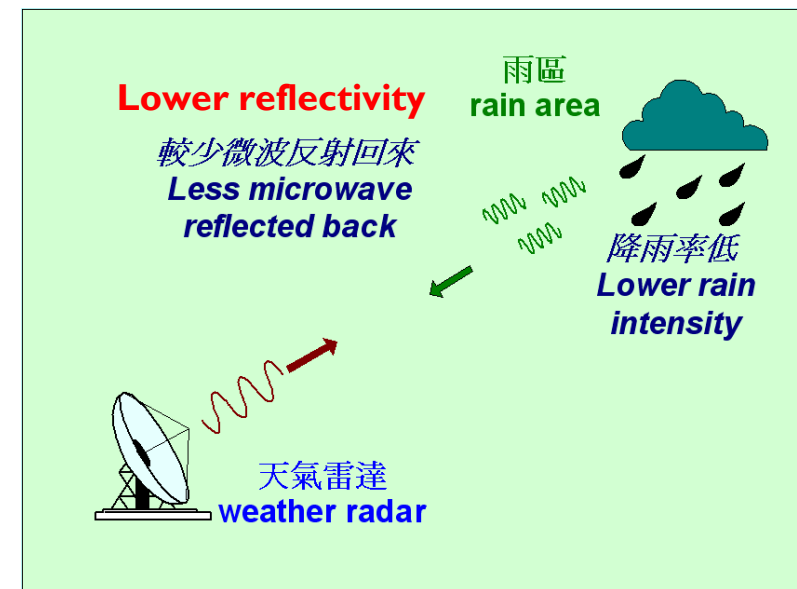
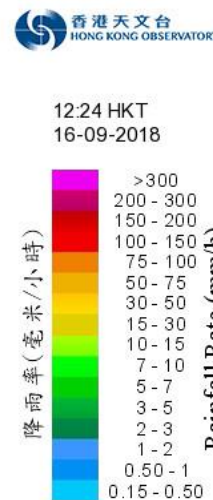
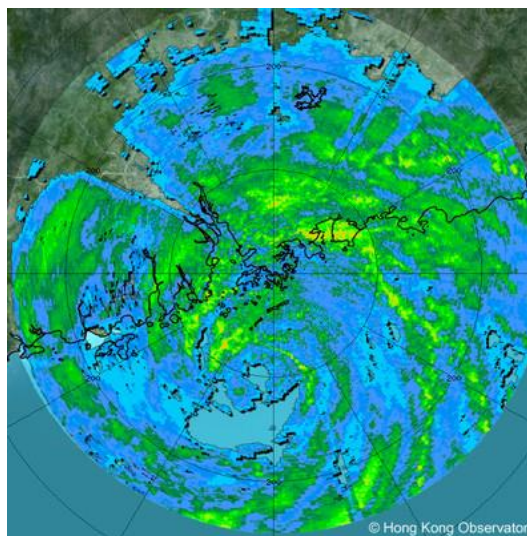
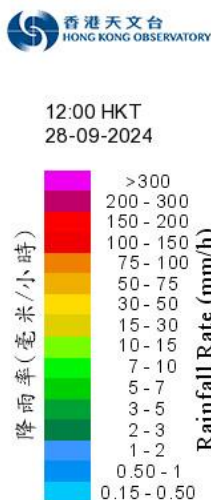
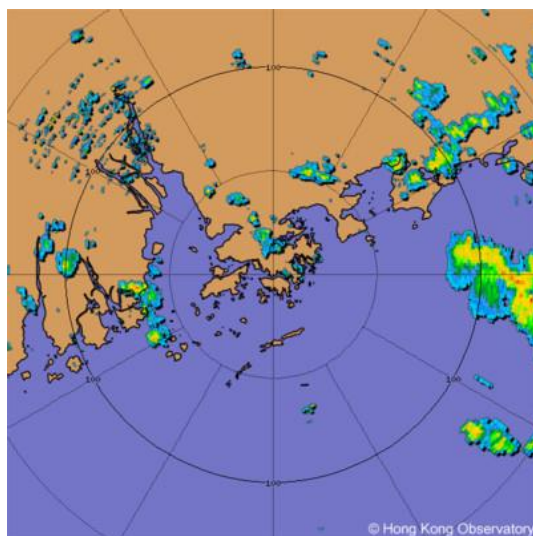
Senior Scientific Officer, Forecast Development Division

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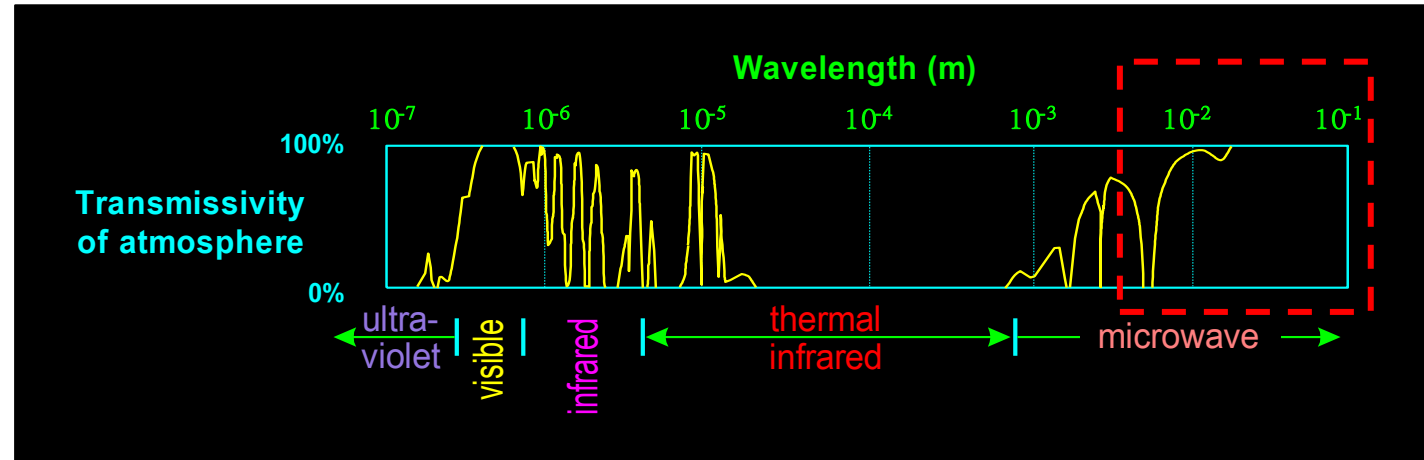
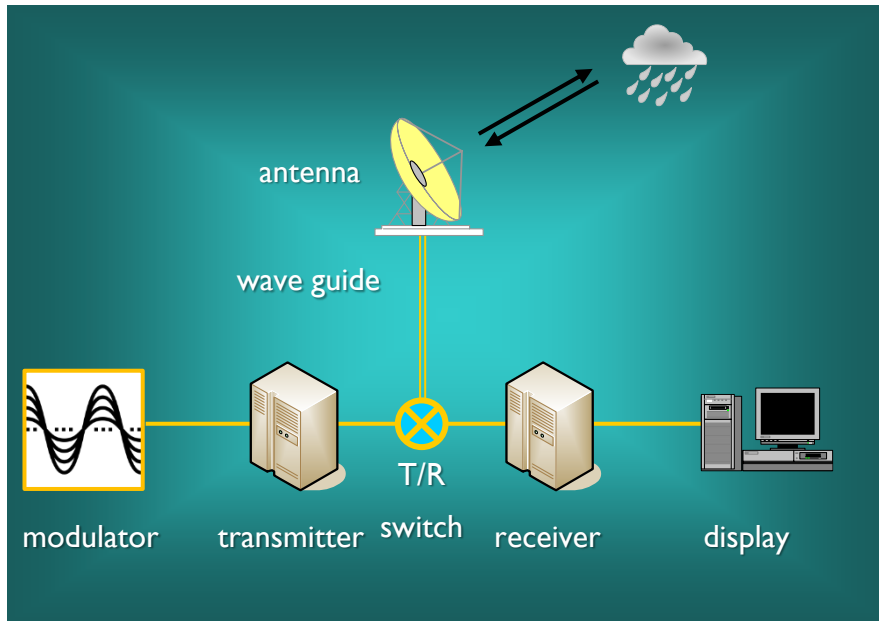
Weather Radar

- **Radar - RAdio Detection And Ranging**
- Weather radar emits microwave radiation into the atmosphere and receives the reflected radiation called echoes from water droplets in the air
 - Microwave in the solar radiation and the Earth's emission spectrum is not intense
→ not affecting the operation of weather radar
 - Moving speed of radar echoes (towards or moving away from radar) can be detected based on Doppler effect

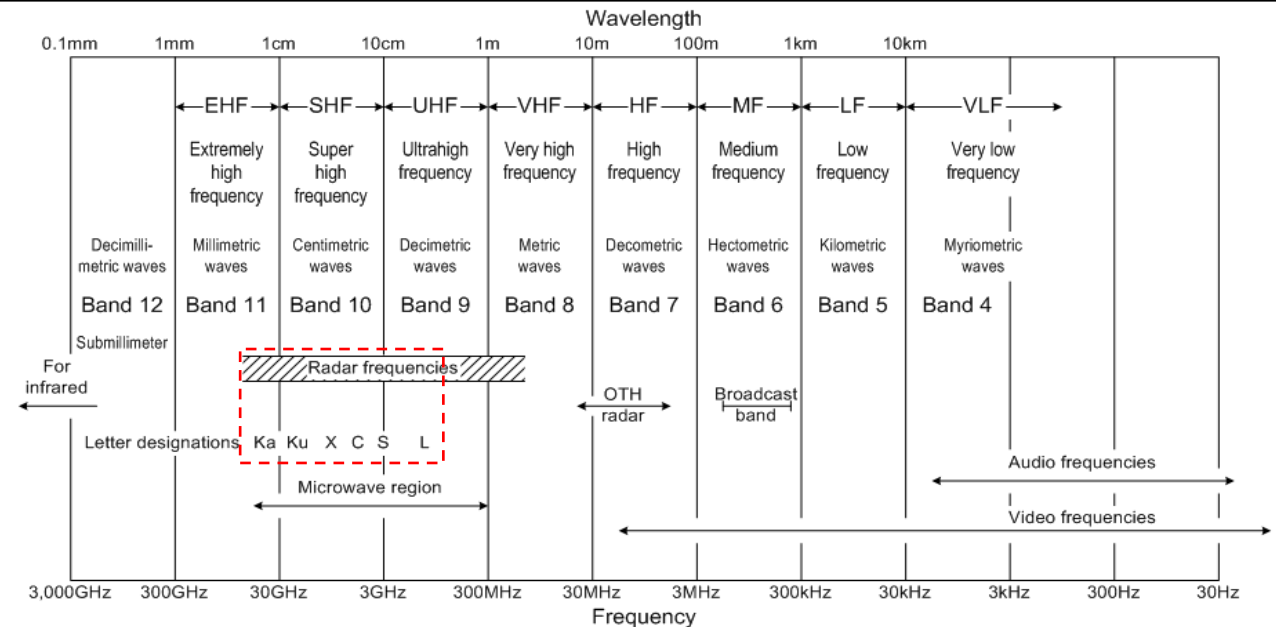


credit: HKO

Operation principle of weather radar (I)

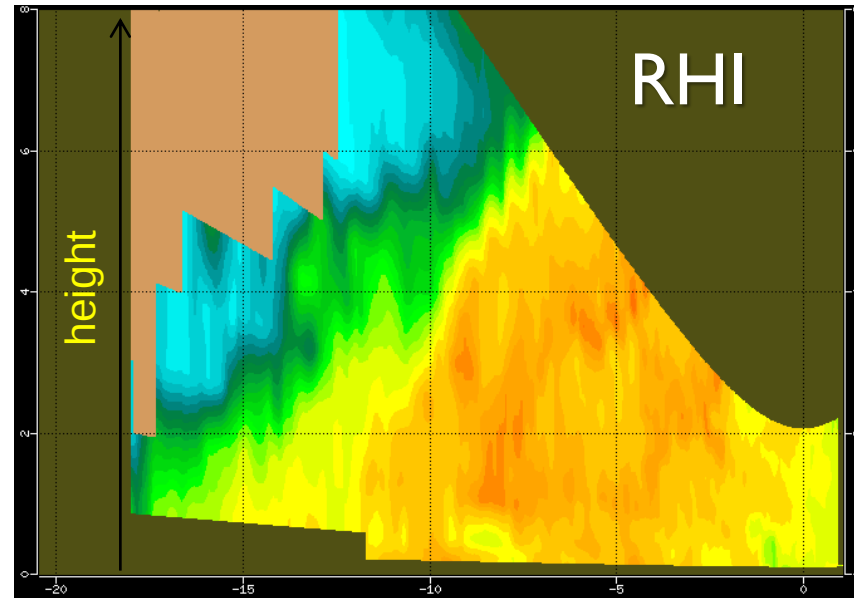
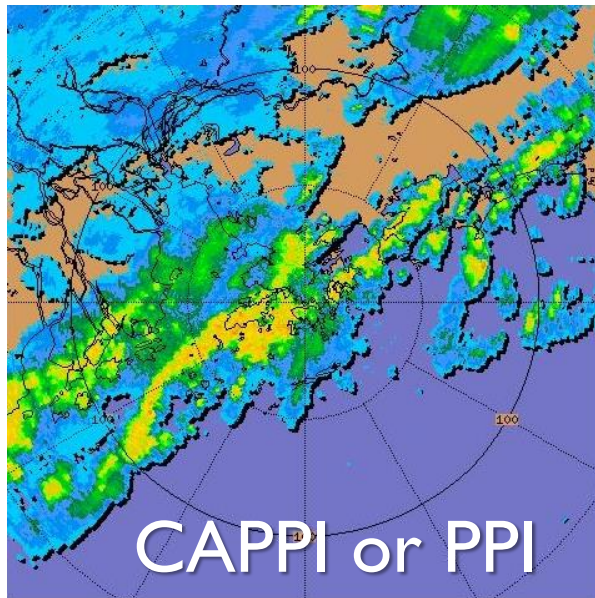


Frequency	Band	Wavelength	Applications
400 - 900 MHz	UHF	0.3 - 0.7 m	wind profiler
1 GHz	L-band	0.3 m	boundary layer wind profiler
2 - 4 GHz	S-band	7-15 cm	long range precipitation radar
4 - 8 GHz	C-band	4-7 cm	long range precipitation radar
8 - 16 GHz	X-band	2-4 cm	precipitation radar
16 - 20 GHz	Ku-band	1-2 cm	precipitation / cloud radar
35 Hz	Ka-band	8.5 mm	precipitation / cloud radar
90 - 100 GHz	W-band	3 mm	cloud radars



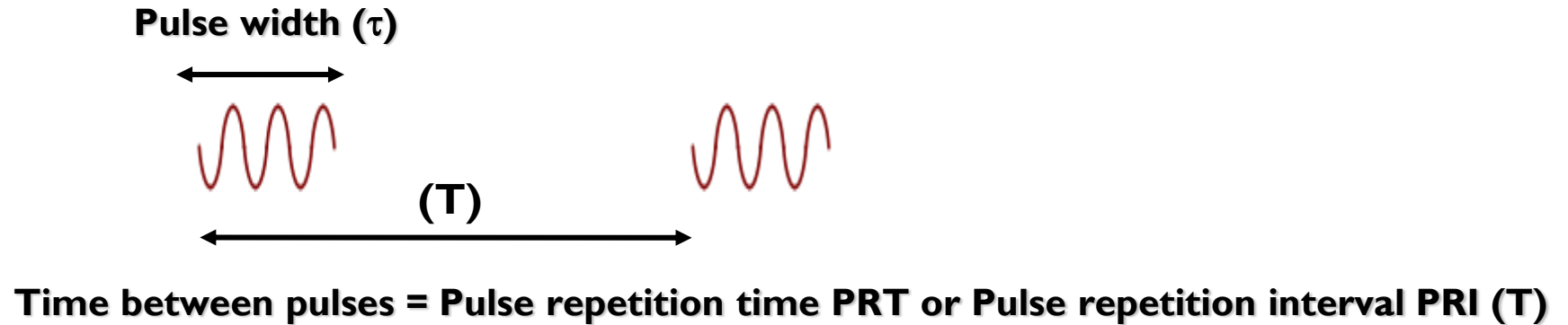
Operation principle of weather radar (2)

- Each conical scan is called a Plan Position Indicators (**PPI**)
- Collection of all conical scans is called a **volume scan**
- Horizontal cross-section is called Constant Altitude PPI (**CAPPI**)
- Vertical cross-section is called Range Height Indicator (**RHI**)



Operation principle of weather (3)

Most weather radars are pulsed radars, i.e. sending out pulses of microwave.



$$\text{Pulse repetition frequency (PRF)} = 1/T$$

- Pulse width τ is usually $\sim$ micro-second (10^{-6} s)
- Longer pulse width means more energy being transmitted, can improve detection of weaker echoes at longer range.
- Longer pulse limits the spatial resolution of radar data
- PRF (inverse of PRT) is usually 100 – 3,000 Hz
- Smaller PRF (longer PRT) enables detection of echoes to greater distance (before emission of next pulse)

Operation principle of weather radar (4)

The received power (P_R) at the radar of the returned microwave due to scattering of raindrops can be derived as the following radar equation:

$$P_R = \underbrace{\left[\frac{c\pi^3}{1024 \ln(2)} \right]}_{\text{constant}} \times \underbrace{\left[\frac{P_T G^2 \theta^2 \Delta\tau}{\lambda^2} \right]}_{\text{radar characteristics}} \times \underbrace{\left[\left(\frac{|K|}{r} \right)^2 z \right]}_{\text{atmospheric characteristics}} = \frac{C}{r^2} z$$

$z = \sum D_i^6$ reflectivity factor
 D = Diameter of raindrops

Introduce a new parameter **reflectivity**, which is a logarithmic parameter measured in unit of dBZ:

$$Z = 10 \log_{10} \left(\frac{z}{1 \text{ mm}^6 / \text{m}^3} \right)$$

Reflectivity factor **z** is related to the **rainfall rate R** by an empirical relation, **z-R relation**:

$$z = a R^b$$

z in unit of mm^6/m^3 ; R in unit of mm/h

For precipitation due to stratiform clouds 層狀雲, the relation is known as the **Marshall-Palmer relation**:

$$z = 200 R^{1.6}$$

➔ Accurate estimation of coefficient values in z-R relationship is important for monitoring and forecasting rainfall from weather radars

Reflectivity and Rainfall Rate

Reflectivity factor (Z) measured by weather radar is the sixth moment of drop size distribution N(D) (D=drop diameter in mm):

$$Z = \int_0^{\infty} N(D) D^6 dD$$

Rain rate (R) is given by:

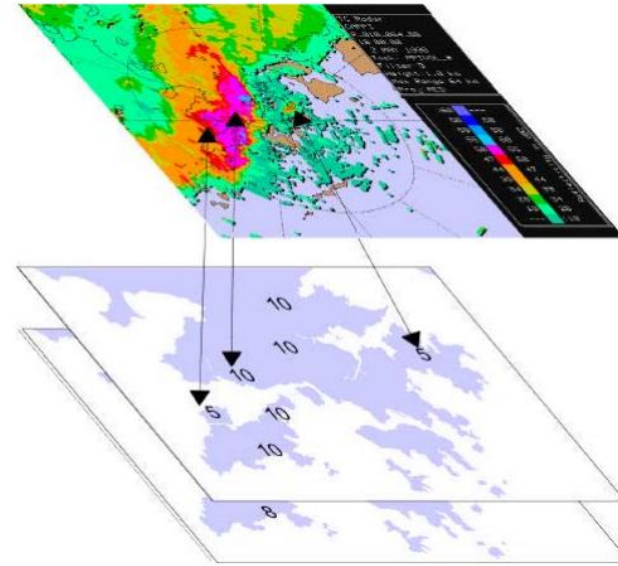
$$R = \frac{\pi}{6} \int_0^{\infty} N(D) D^3 V(D) dD$$

V(D) is the fall velocity of particles of size D

$$Z = Z(R, N(D))$$

an empirical relationship on Z-R:

$$z = a R^b$$



$$Z = aR^b$$

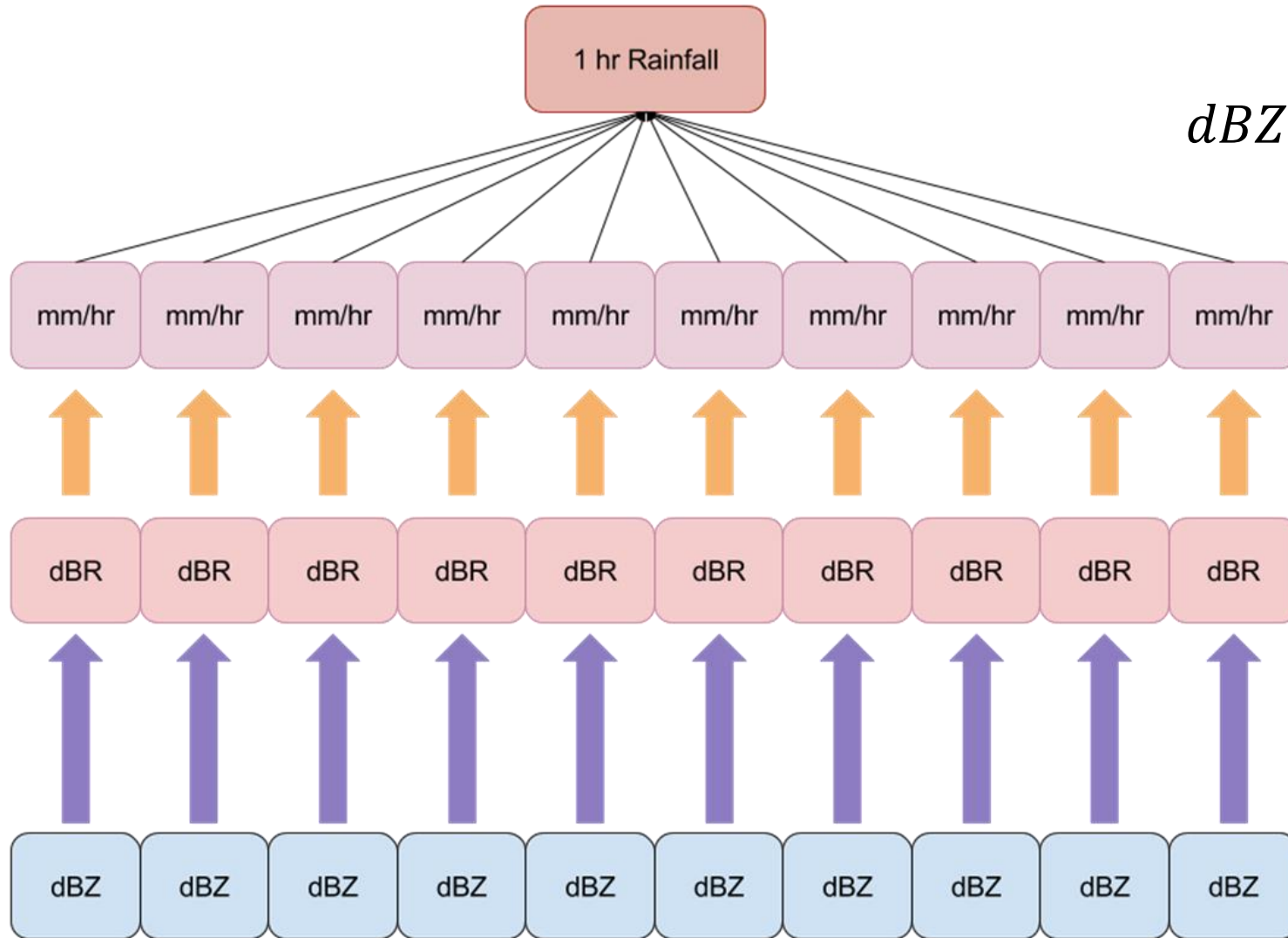
$$dBZ_i = 10 \log(a) + b \, dBR_i$$

$$dBZ = 10 \log_{10} Z$$

$$dBR = 10 \log_{10} R$$

From Radar Reflectivity to Rainfall

$$Z = aR^b$$
$$dBZ = 10 \log(a) + b dBZ$$



With the Z-R
relation, can
convert dBZ →
dBR → hourly
rainfall

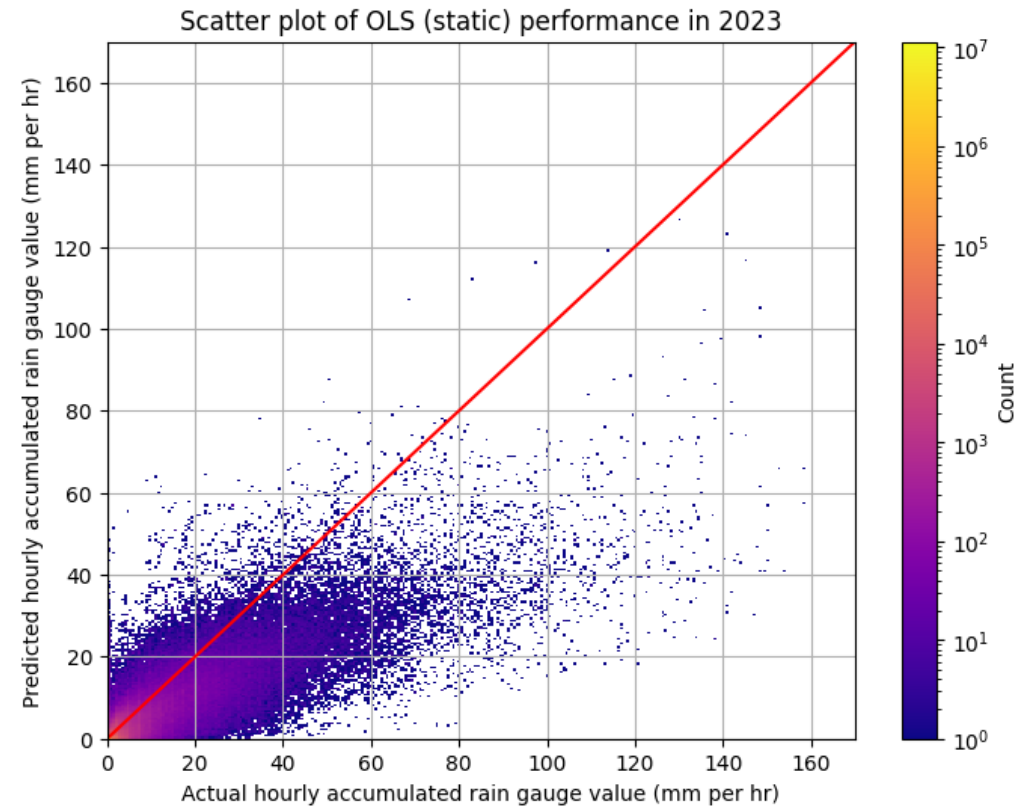
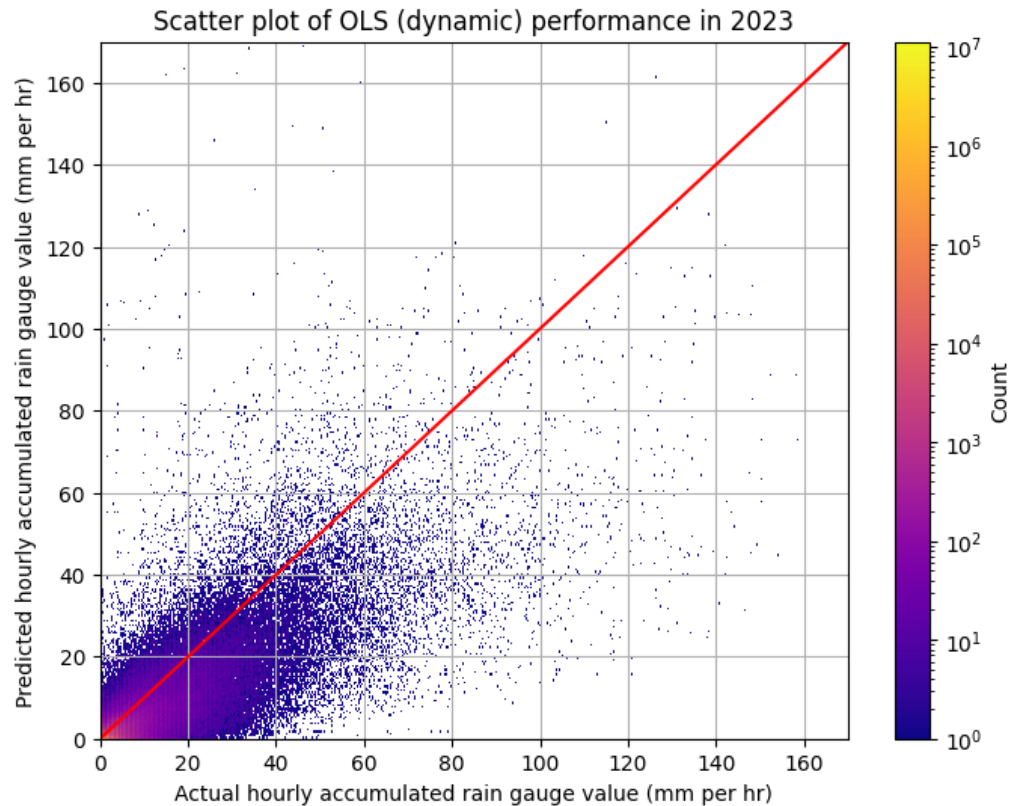
10 Radar Images → 1 image every 6 Minutes → 1 hr rainfall

Scatterplots of estimated radar rainfall vs actual

$$z = a R^b$$

dynamical update a and b

static a and b based on historical data

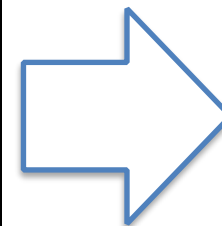
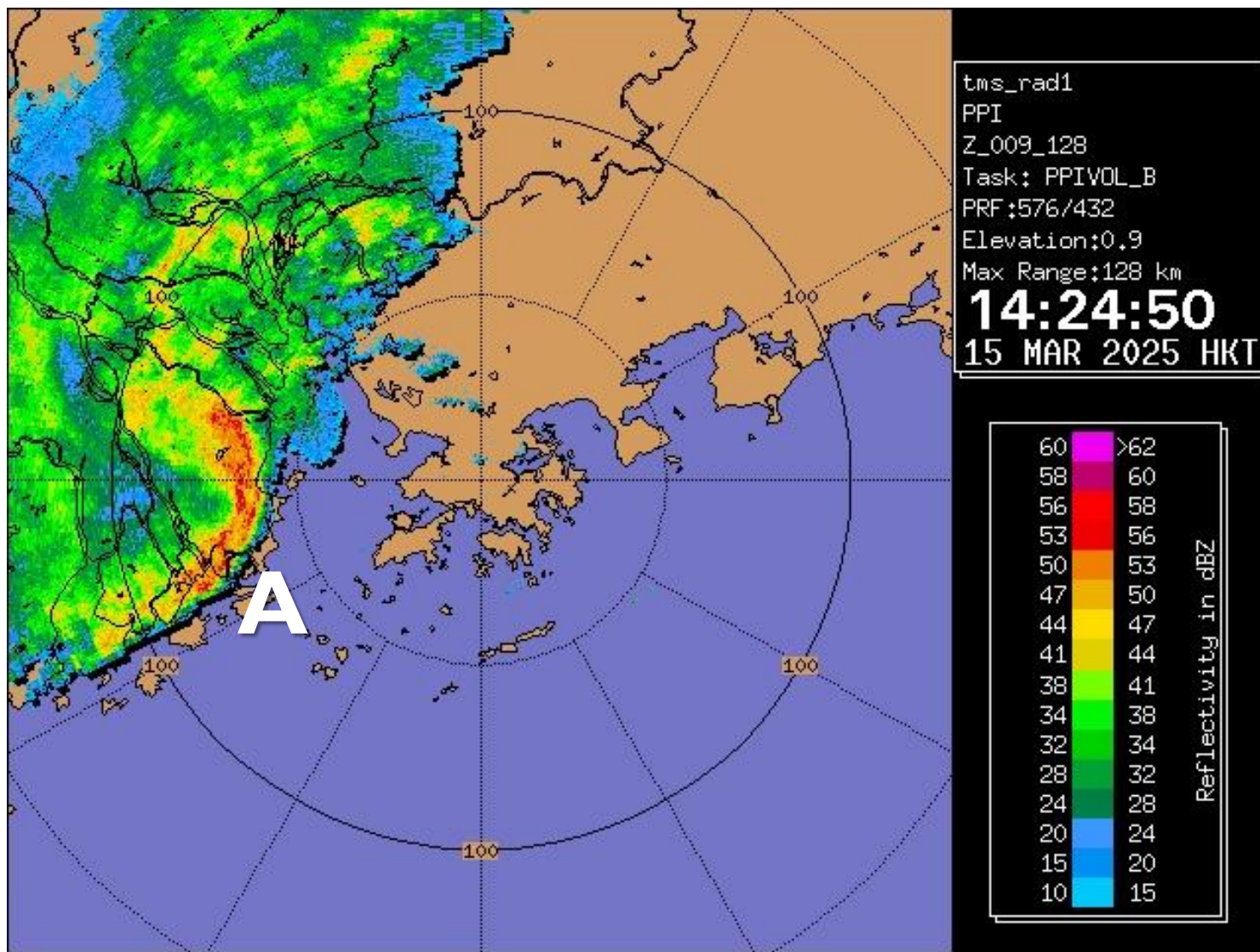


Converting Radar Reflectivity Image to Rainfall Rate

In weather radar image of reflectivity, different reflectivity (in dBZ) is assigned different colours for identifying where heavy rain is located.

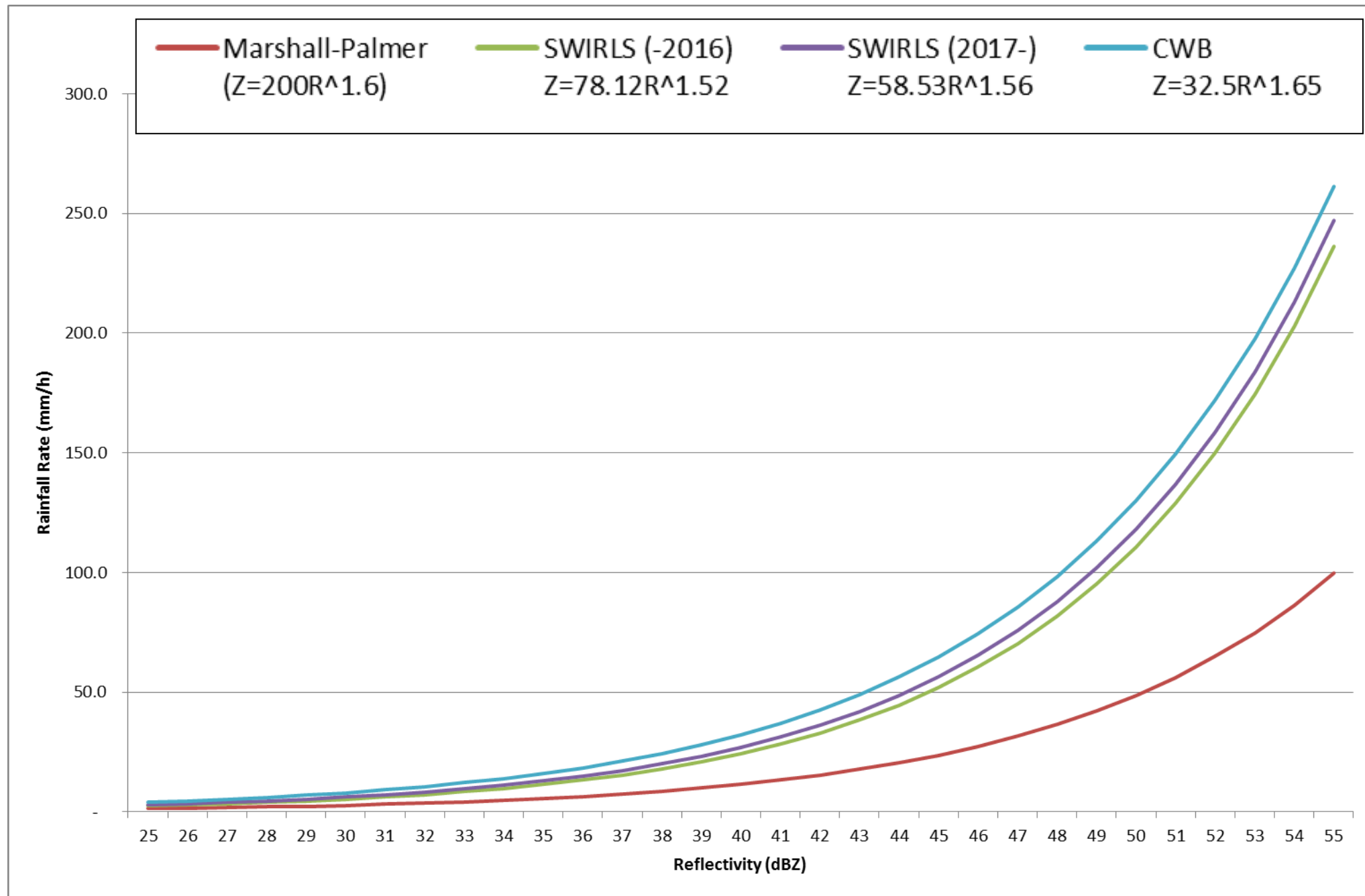
$$dBZ = 10 \log_{10} Z$$

Level	dBZ	Description	Rainfall rate in mm/h ($Z = 200 R^{1.6}$)	Rainfall rate in mm/h ($Z = 300 R^{1.4}$)	Rainfall rate in mm/h ($Z = 58.8 R^{1.56}$)
1	18-30	Light rain			
2	30-41	Moderate rain			
3	41-46	Heavy rain			
4	46-50	Very heavy rain			
5	50-57	Intense rain			
6	>57	Extreme rain			

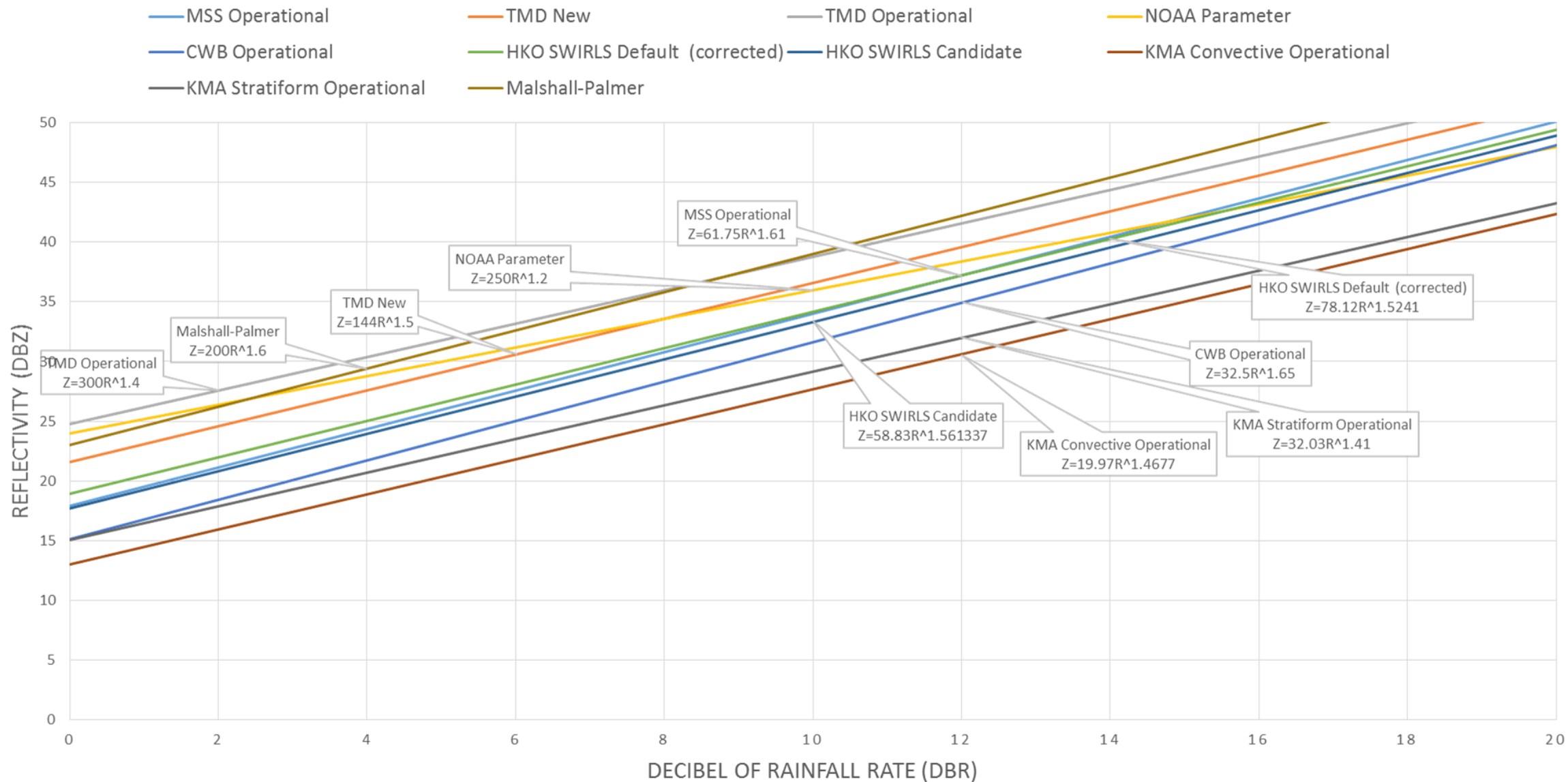


1. Estimate the maximum rainfall rate (mm/hr) to the west of the Pearl River Estuary (area A)
2. Do you expect the actual 1 hour accumulated rainfall is similar, larger / smaller than the results in Q1? Explain your answer.

Comparing reflectivity- rainrate (Z-R) relationships



Z-R in other Meteorological Services



Gridded QPE from Radar and Rain Gauge Observations

Barnes Analysis

- interpolation with Gaussian weighting according to distance between data & estimation point
- consider correction using residuals and grouping of rain gauges

$$B(x_0) = \frac{\sum_{i=1}^{N_0} w_i G_i}{\sum_{i=1}^{N_0} w_i}$$

$$w_i = \exp\left(\frac{-h_i^2}{L^2}\right)$$



B : Barnes estimation (mm)

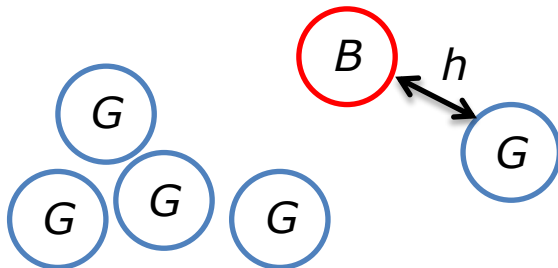
L : radius of influence

N_0 : number of gauge report

G_i : i-th gauge report (mm)

w_i : weight of i-th gauge

h_i : distance between gauge and estimation point



Co-kriging Analysis

- extends from ordinary geostatistical kriging technique and take into account both radar reflectivity and rain gauge data
- consider error characteristics (spatial covariance and correlation) of rain gauge measurements and radar reflectivity field

$$\text{co-Kriging estimate: } K(x_0) = \sum_{i=1}^{N_0} \lambda_i(x_0) G_i + \sum_{j=1}^{M_0} \lambda_j(x_0) R_j$$

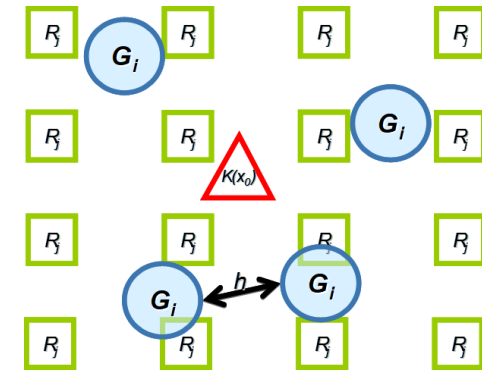
$$\text{seek to minimize: } \sigma^2 = E \left\{ [K(x_0) - G(x_0)]^2 \right\}$$

$$\text{subject to constraints: } \sum_{i=1}^{N_0} \lambda_i(x_0) = 1 \quad \& \quad \sum_{j=1}^{M_0} \lambda_j(x_0) = 0$$

Solution:

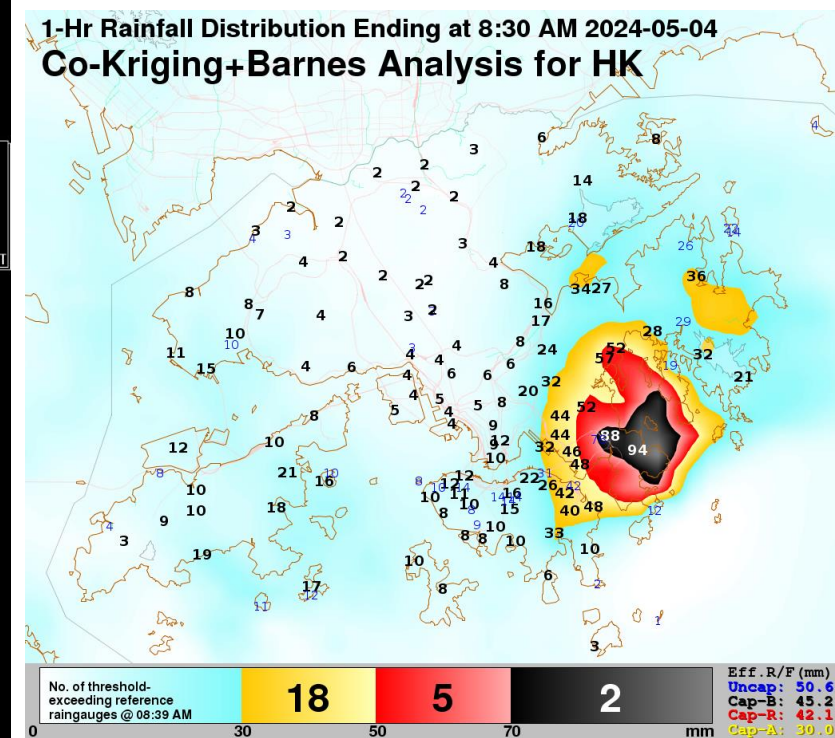
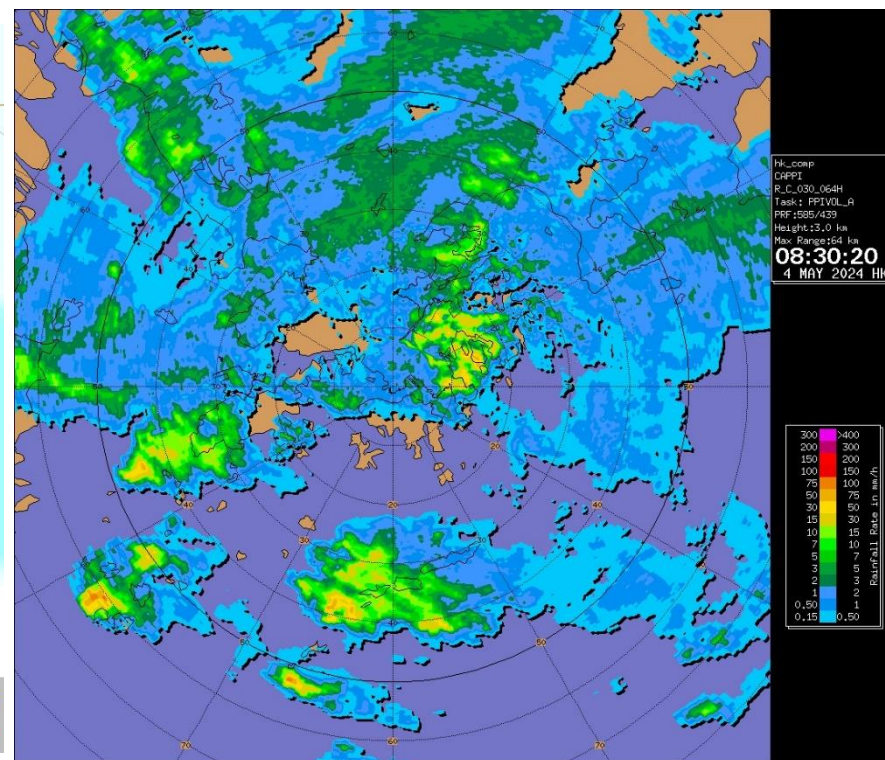
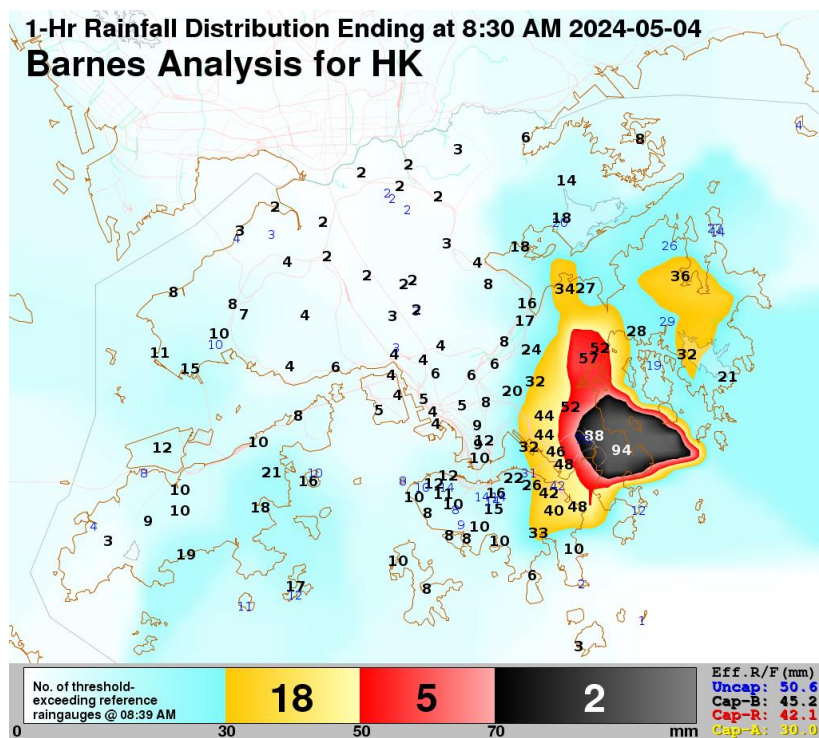
$$\sum_{i=1}^{N_0} \lambda_i(x_0) \gamma_{GG}(x_n, x_i) + \sum_{j=1}^{M_0} \lambda_j(x_0) \gamma_{GR}(x_n, x_j) + \mu_G(x_0) = \gamma_{GG}(x_n, x_0), \quad \text{for } n = 1, \dots, N_0$$

$$\sum_{i=1}^{N_0} \lambda_i(x_0) \gamma_{RG}(x_m, x_i) + \sum_{j=1}^{M_0} \lambda_j(x_0) \gamma_{RR}(x_m, x_j) + \mu_R(x_0) = \gamma_{RG}(x_m, x_0), \quad \text{for } m = 1, \dots, M_0$$



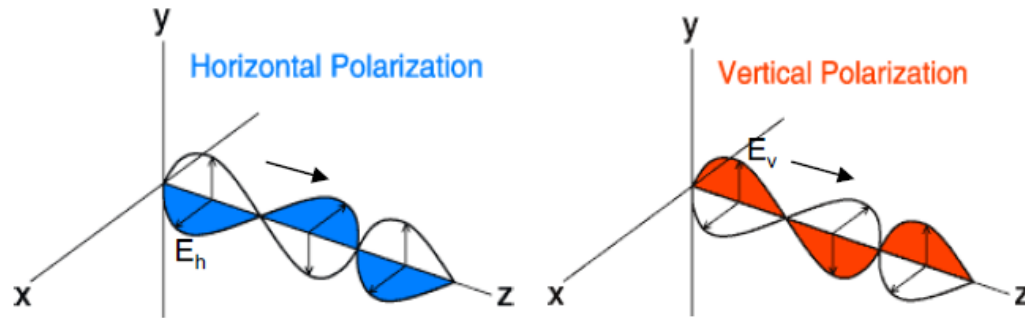
Reference: <https://www.hko.gov.hk/publica/reprint/r968.pdf>

Example of Barnes vs Co-kriging methods



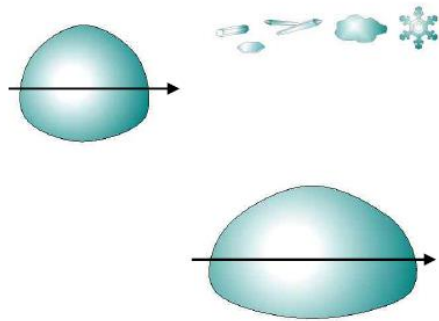
Dual-polarization Radar

- Dual-polarization radar transmit and receive both horizontal and vertical polarized pulses.

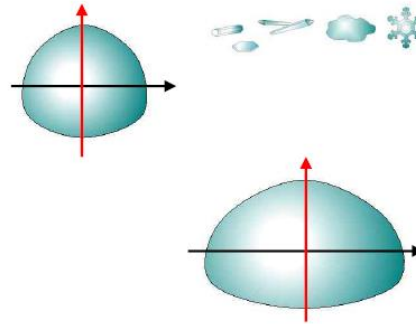


Raw Data

- Reflectivity (Z)
- Velocity (V)
- Spectral Width (W)
- Differential Reflectivity (ZDR)
- Differential Phase (Φ_{DP})
- Specific Differential Phase (K_{DP})
- Correlation Coefficient (ρ_{hv})



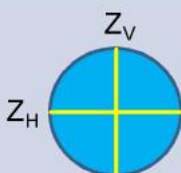
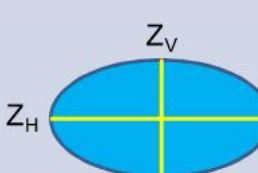
Single-polarization



Dual-polarization

Differential Reflectivity (ZDR)

- Useful indicator of the average drop shape of the dominant hydrometeor within the resolution volume

<u>Spherical</u> (drizzle, small hail, etc.)	<u>Horizontally Oriented</u> (rain, melting hail, etc.)	<u>Vertically Oriented</u> (i.e. vertically oriented ice crystals)
		
$Z_H \sim Z_V$	$Z_H > Z_V$	$Z_H < Z_V$
$Z_H - Z_V \sim 0$	$Z_H - Z_V > 0$	$Z_H - Z_V < 0$
ZDR ~ 0 dB	ZDR > 0 dB	ZDR < 0 dB

Physical Interpretation of ZDR

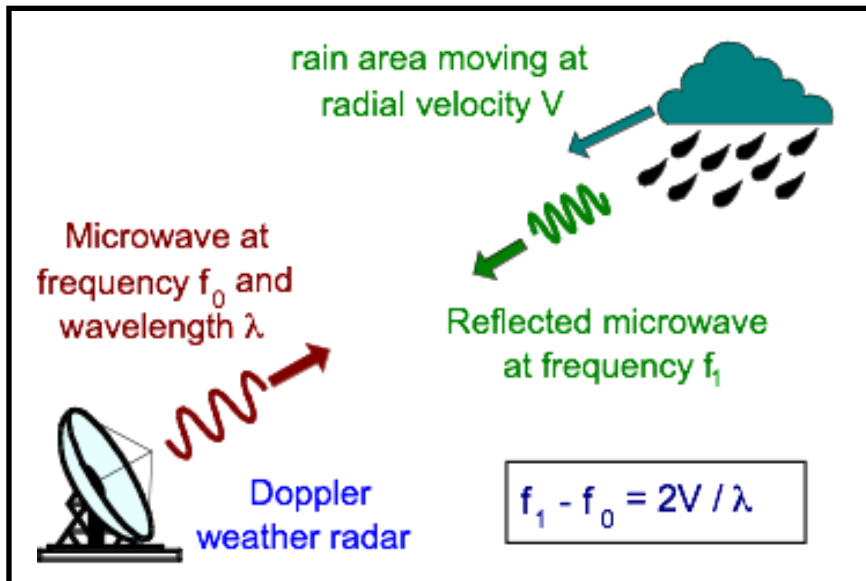
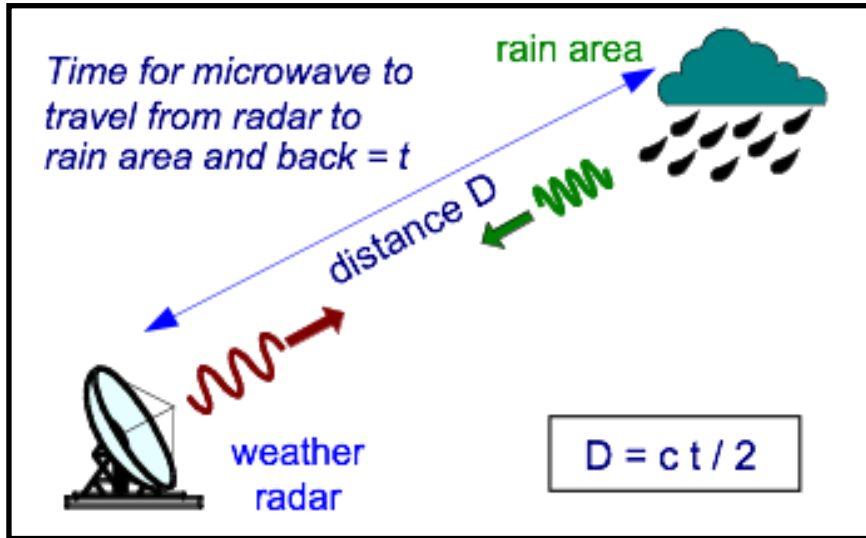
- Rain
 - appears spherical to radar
 - ZDR ~ 0 dB
- Hail tends to tumble
 - appears spherical to radar
 - ZDR ~ 0 dB
- Small and completely water-coated hail
 - appears as giant raindrop
 - ZDR ~ 5 – 6 dB
- Non-met echoes
 - Ground clutter: very noisy
 - Biological scatterers: less noisy, orientation with flight direction

Major Axis Diameter (mm)	Image	ZDR (dB)
< 0.3 mm		~ 0.0 dB
1.35 mm		~ 1.3 dB
1.75 mm		~1.9 dB
2.65 mm		~2.8 dB
2.90 mm		~3.3 dB
3.68 mm		~4.1 dB
4.00 mm		~4.5 dB

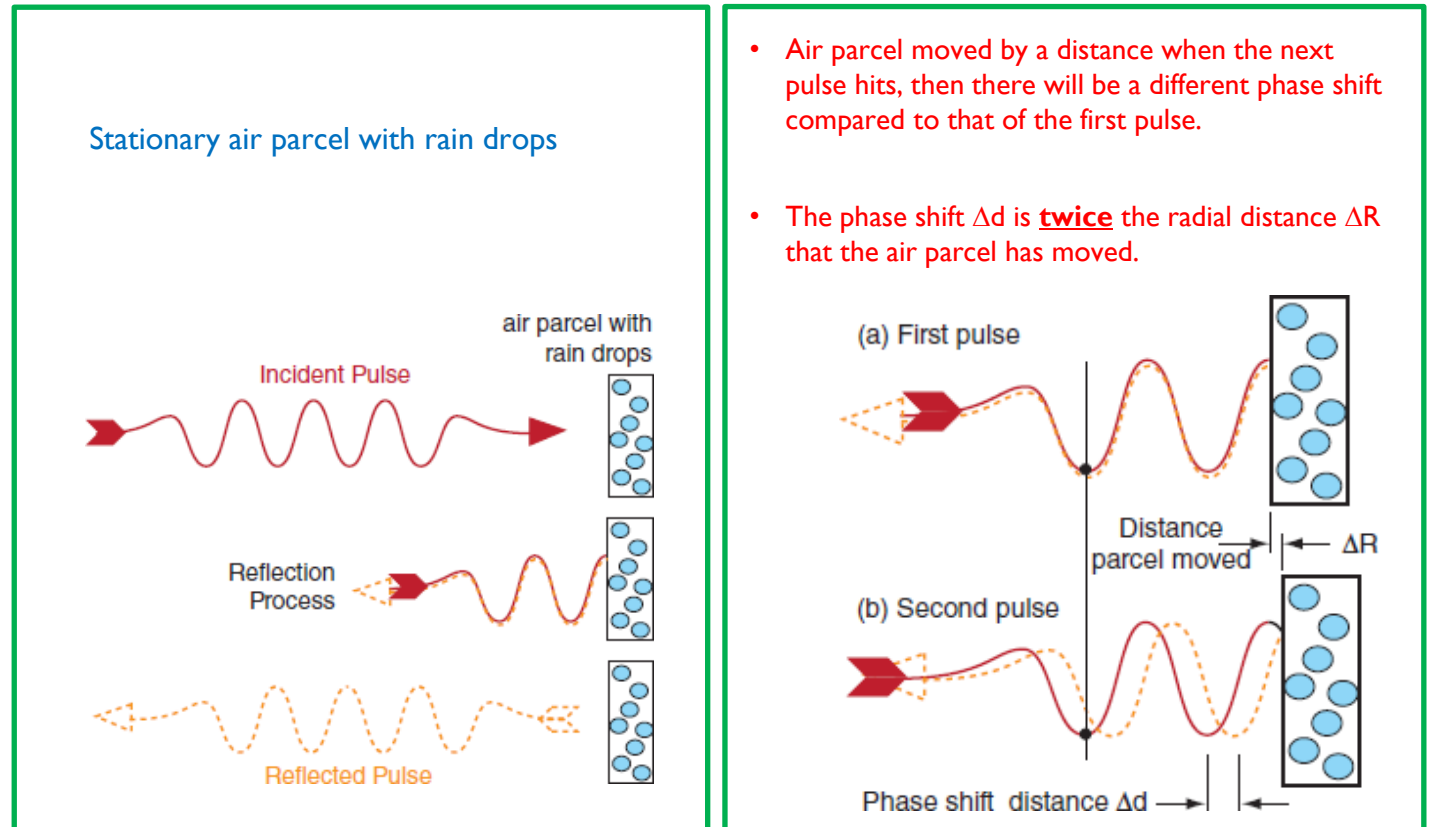
Data from Wakimoto and Bringi (1988)

➔ Dual-pol parameters can improve identification of rain drops and types of hydrometeors, and estimation of rainfall from radar

Doppler Velocity

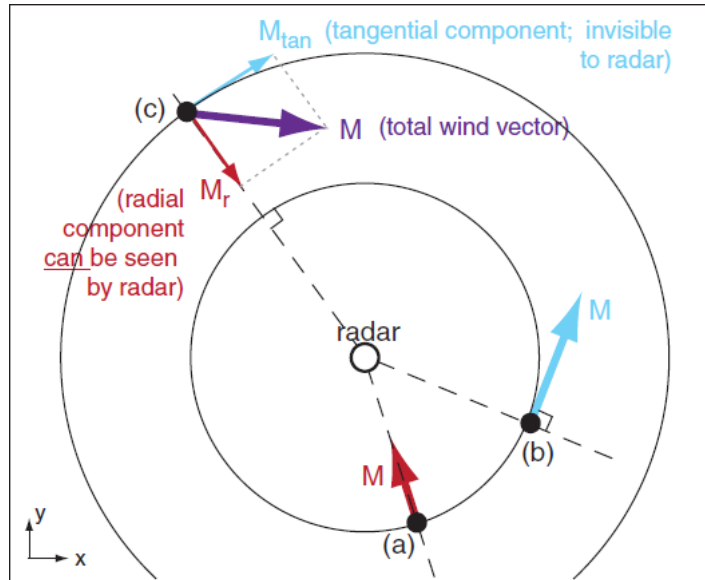


- Noted that the Doppler frequency shift is rather small compared to the transmitted frequency of microwave (**why?**)
- Doppler radars detect air motion by measuring phase shift of microwaves

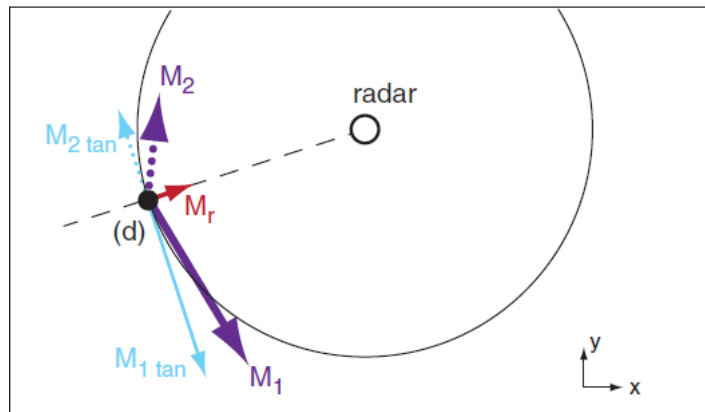


Credit: Stull

Doppler Velocity



Credit: Stull



Question: How could the true wind field be determined using radar?

Given a known wind vector ($\mathbf{M}$) at a point, only the radial component of the total wind (M_r) is detected by Doppler weather radar.

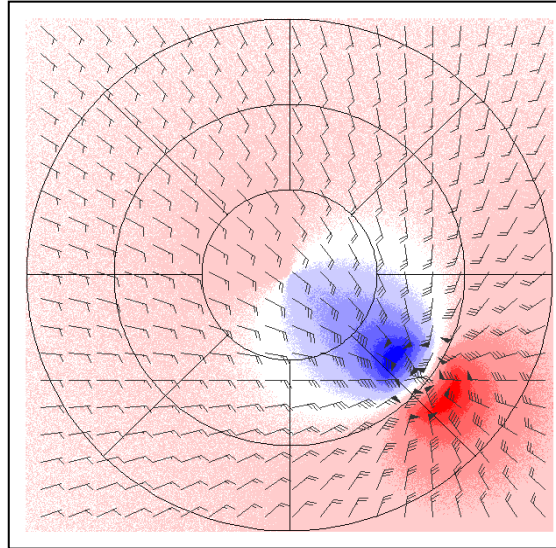
- At point (a) the total wind vector $\mathbf{M}$ is along the radial line, hence the radar can detect the whole wind.
- At point (b) the total wind vector $\mathbf{M}$ is tangent to the circle, hence the radar sees zero wind there.
- At point (c) the total wind vector $\mathbf{M}$ has a radial component M_r that the radar detects, and a tangential component M_{tan} that is invisible. Thus only part of the total wind is detected there.

Oppositely if the full wind vector is unknown. Beware that an infinite number of true wind vectors can create the same radial component as detected by the Doppler radar.

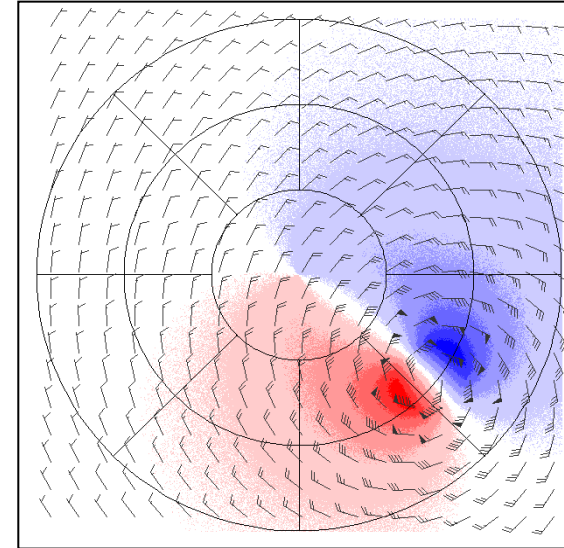
- For example, at point (d) two completely different wind vectors $\mathbf{M}_1$ and $\mathbf{M}_2$ have the same radial component M_r .
- The radar only detects M_r but there is insufficient information to determine the total wind vector (speed) unless under certain specific condition such as the weather system or associated features taking direction of movement in radial direction towards / away from the radar

Examples of wind flow or condition for Doppler radial velocity field
 (warm color +ve / radial outward; cold color -ve / radial inward);
 Radar is located at the centre of the circles.

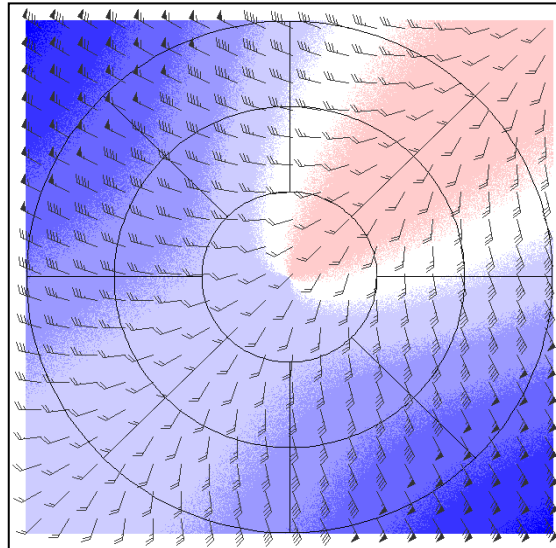
divergent



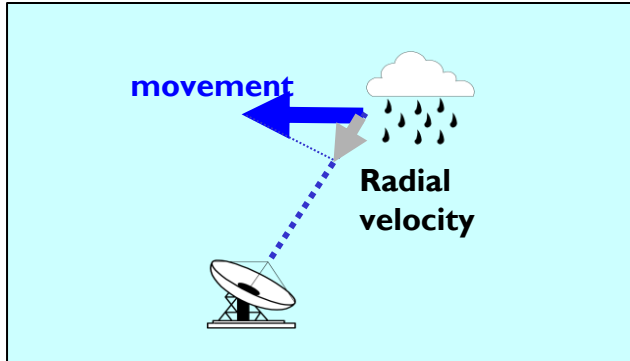
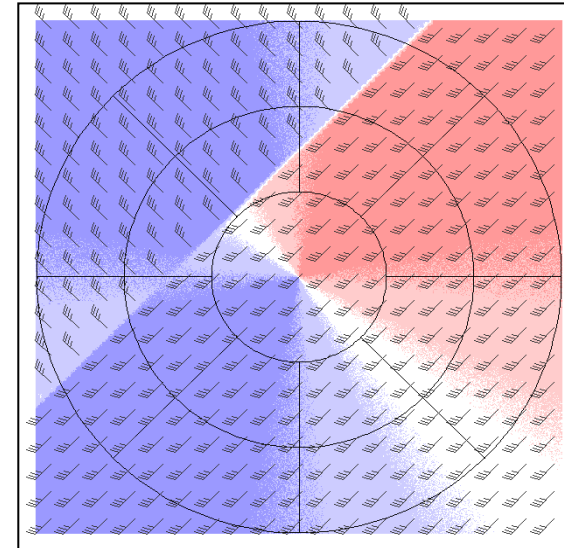
cyclonic rotation



confluent

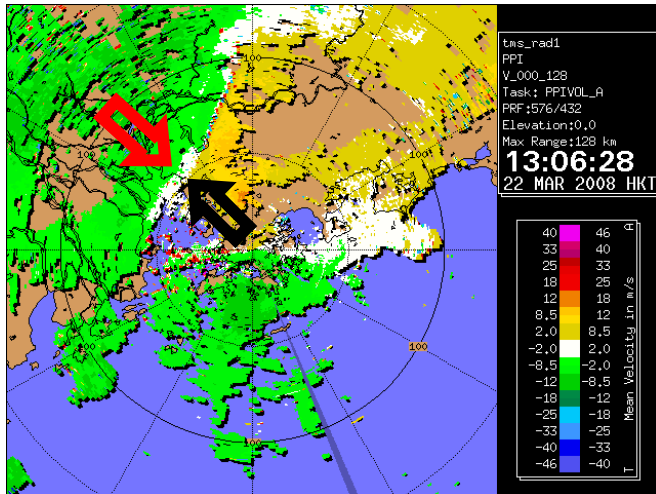
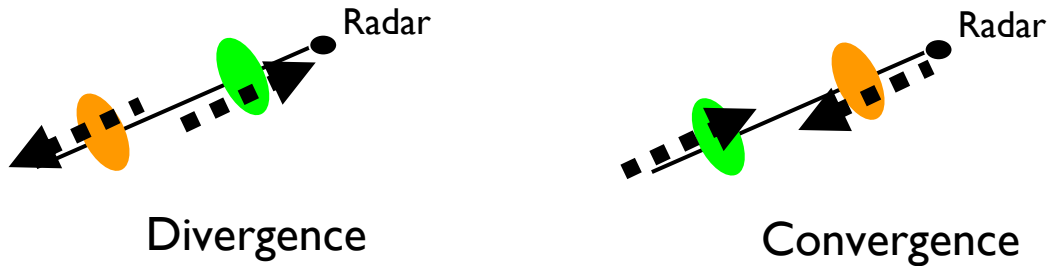


shear-line



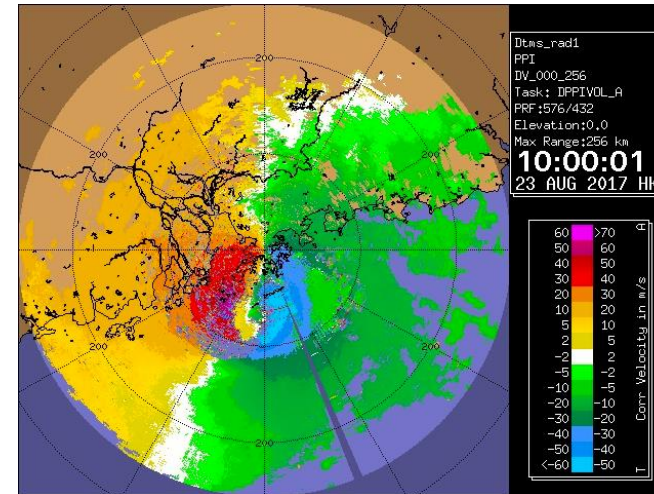
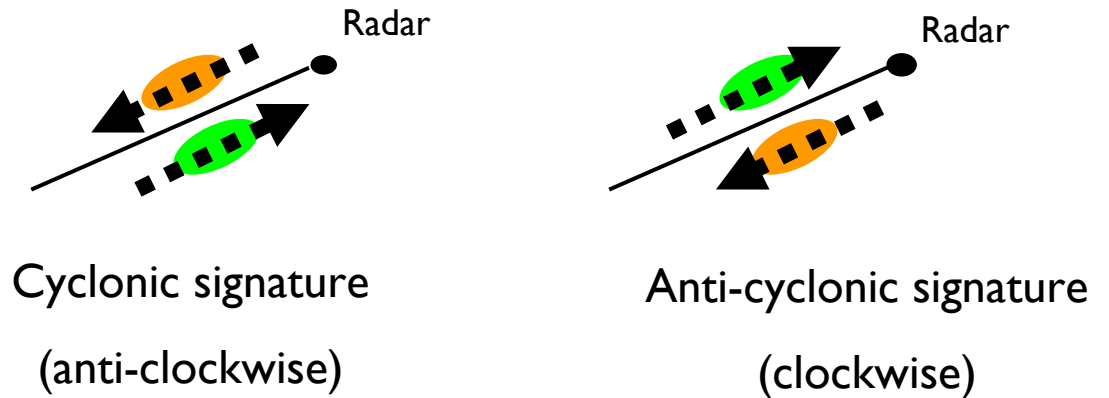
Convergence / Divergence

Look for 'dipoles' of warm/cold colors along a radial to identify convergence/divergence



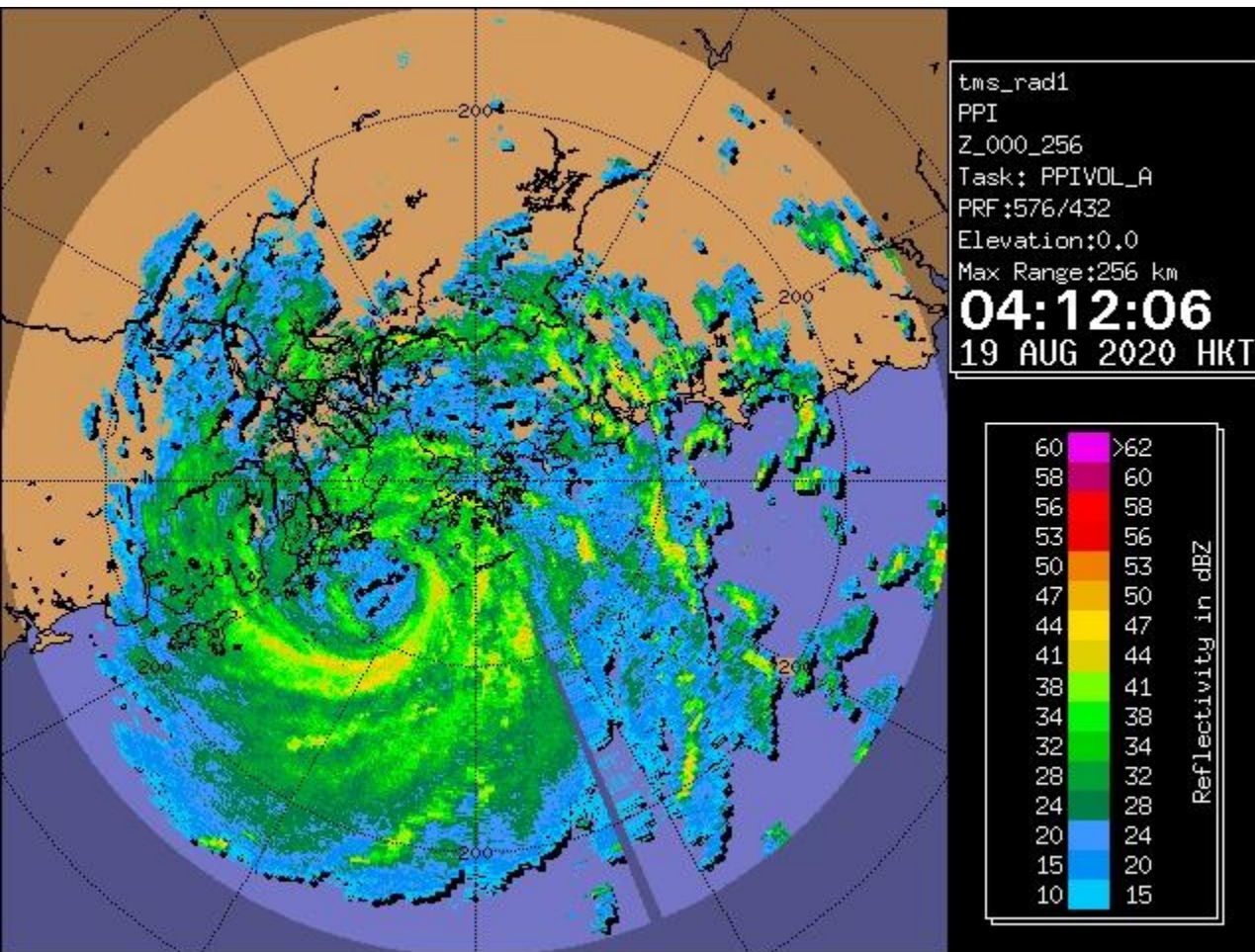
Cyclonic / Anti-cyclonic Vortex

Look for 'dipoles' of warm/cold colors on either side of a radial to identify cyclonic/anti-cyclonic signatures

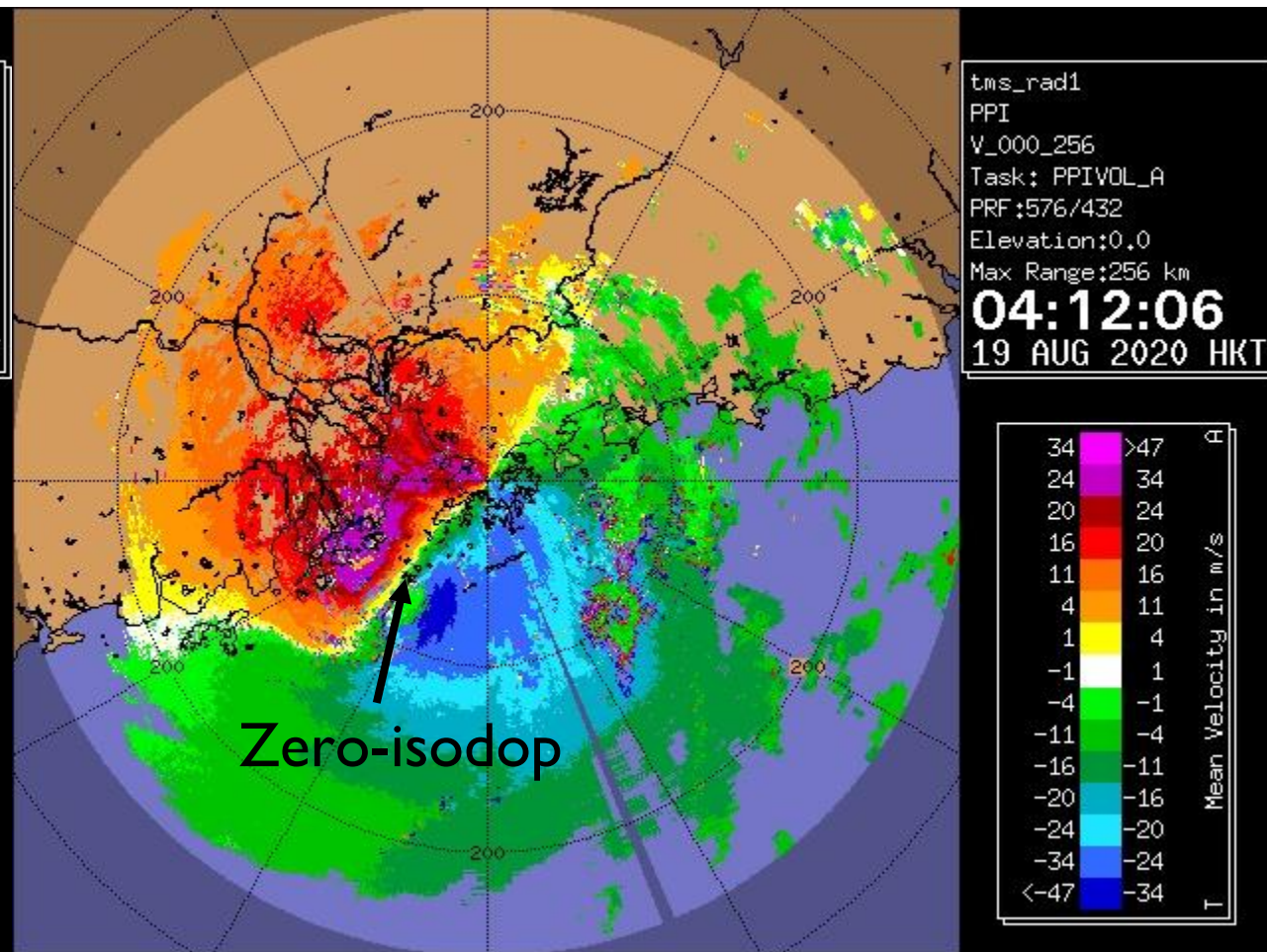


Typhoon Higos (19 Aug 2020)

TMS 0 deg PPI Reflectivity



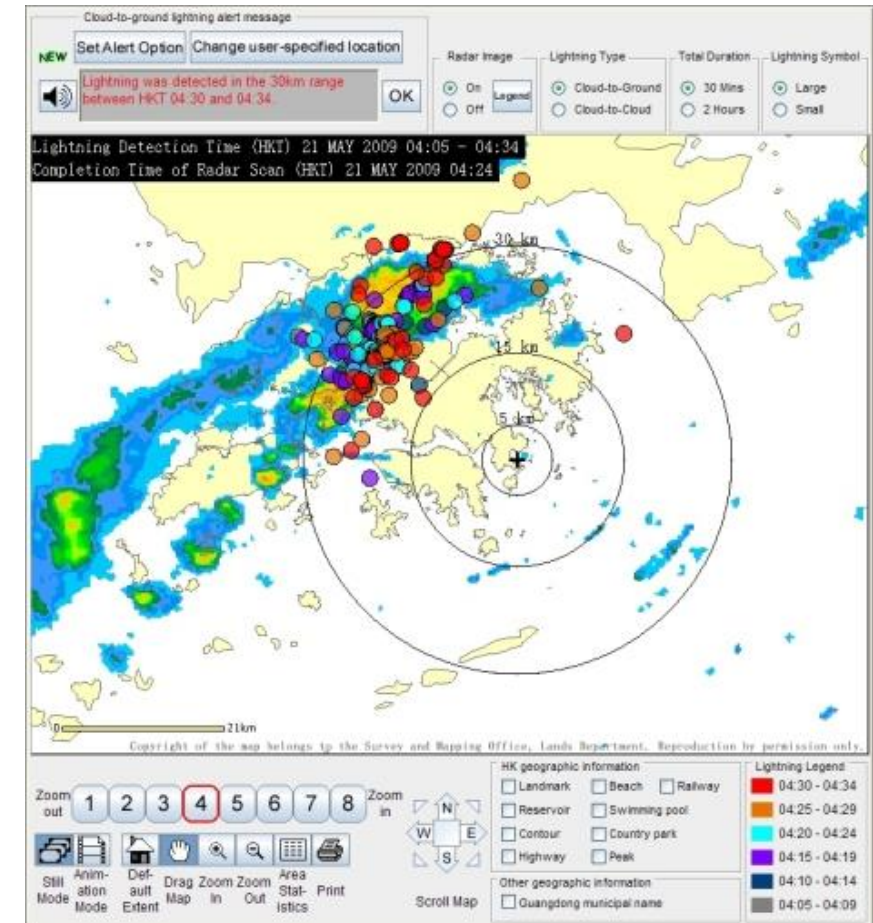
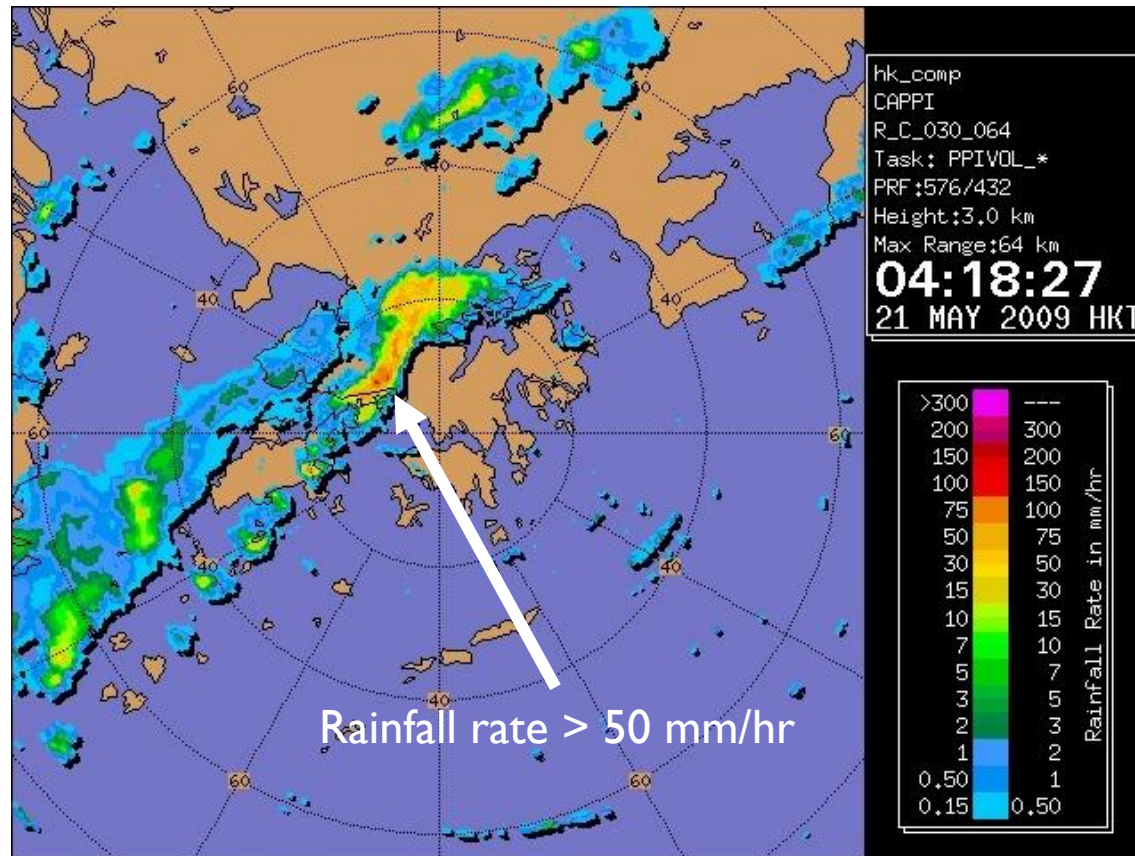
TMS 0 deg PPI Doppler Velocity



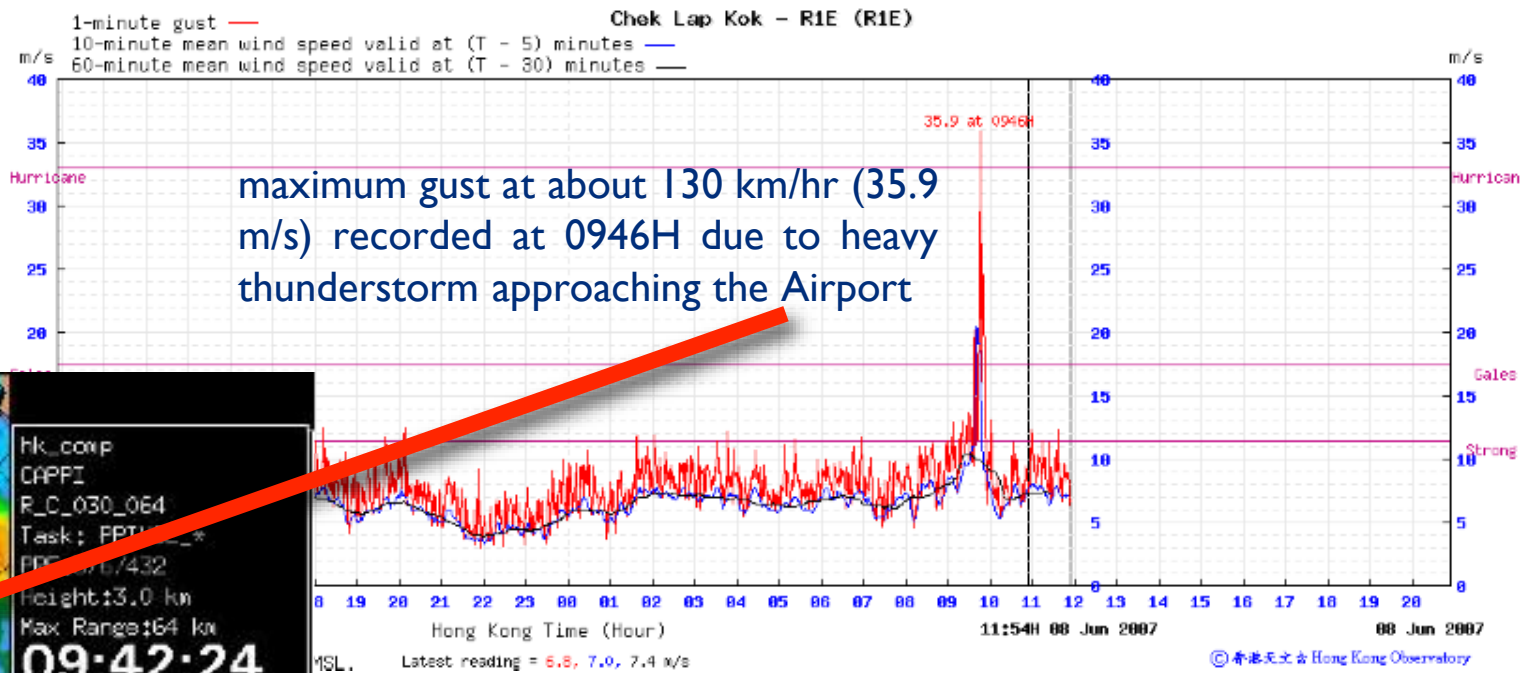
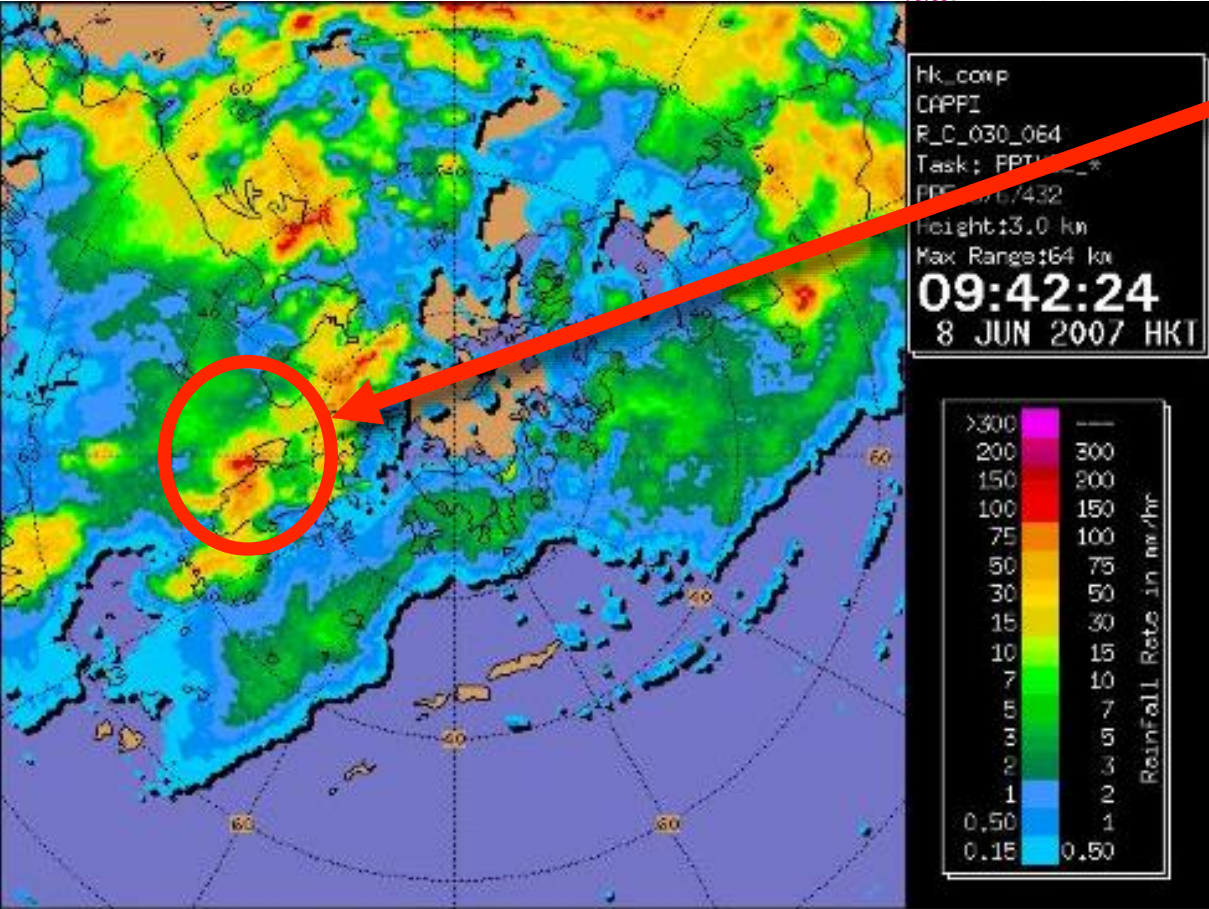
- Thunderstorms are usually associated with **intense echoes** (e.g. greater than 50 mm/hr)
- Lightning location images are helpful to monitor thunderstorms

Lightning location images overlaid on CAPPI Reflectivity

3 KM CAPPI Rainfall Rate



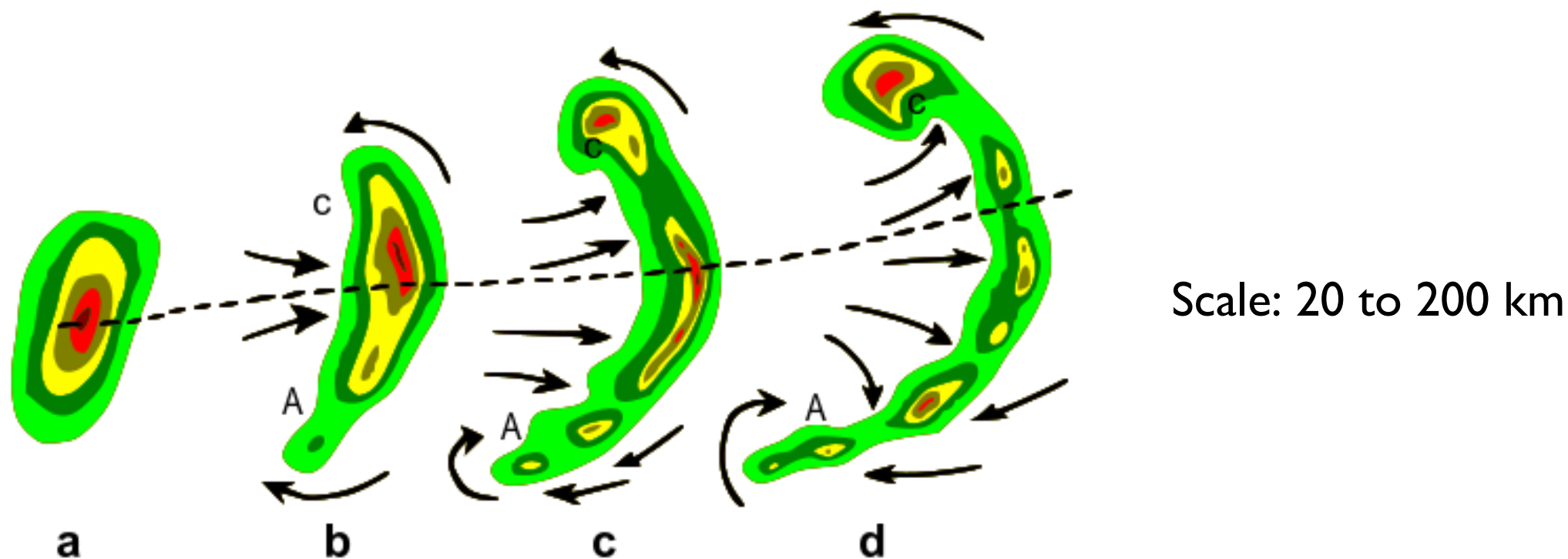
Severe storm



Time series of mean wind and gust recorded at the HKIA during morning on 8 June 2007

credit: HKO

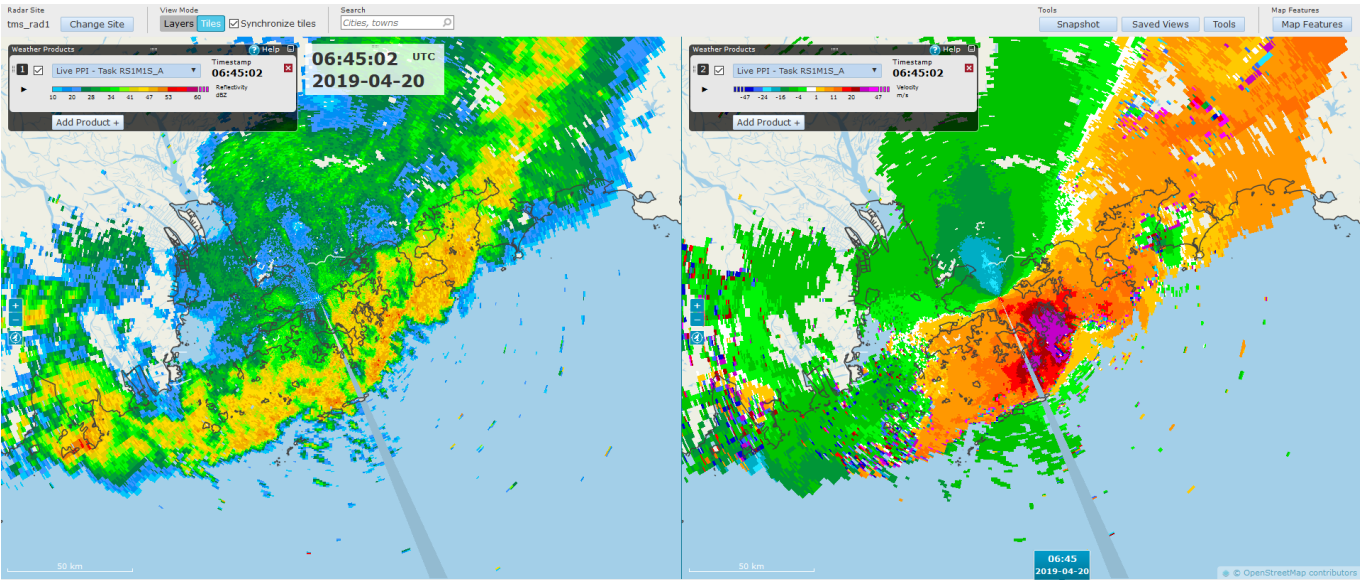
Bow-shaped echoes in a squall line signifying severe convective weather such as violent wind gust



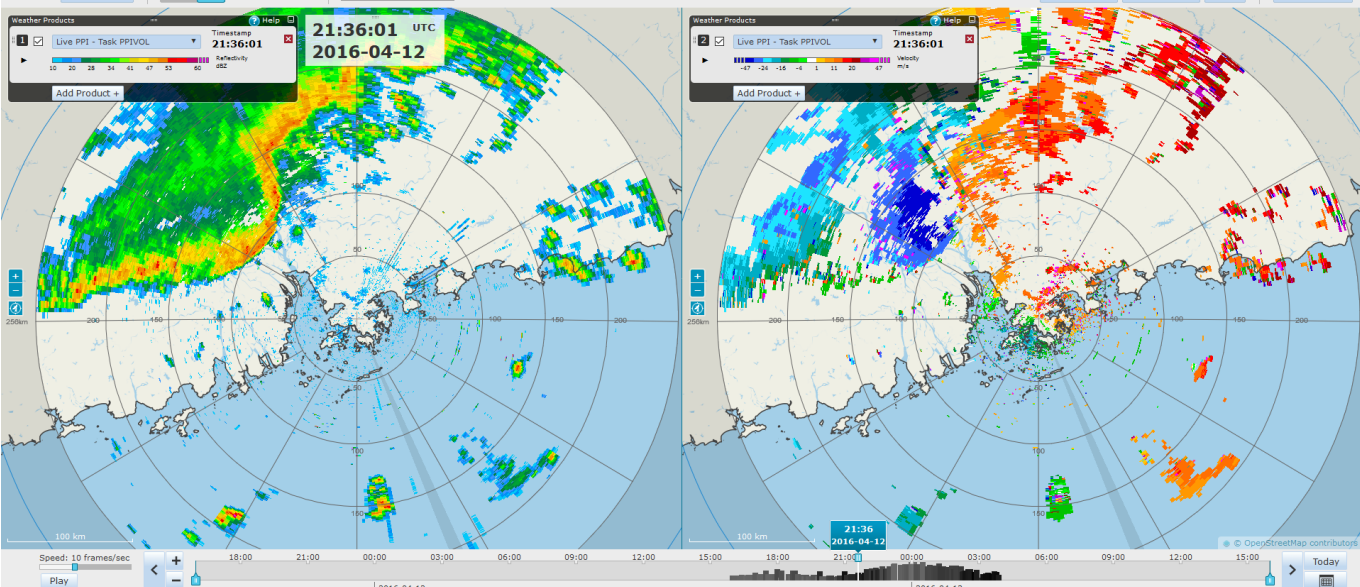
The bow-shaped echo is a result of focusing of the strong flow at the rear of the system.

Bow-shaped echoes in a squall line signifying potential damaging winds

Case I: 2019-04-20



Case II: 2016-04-12

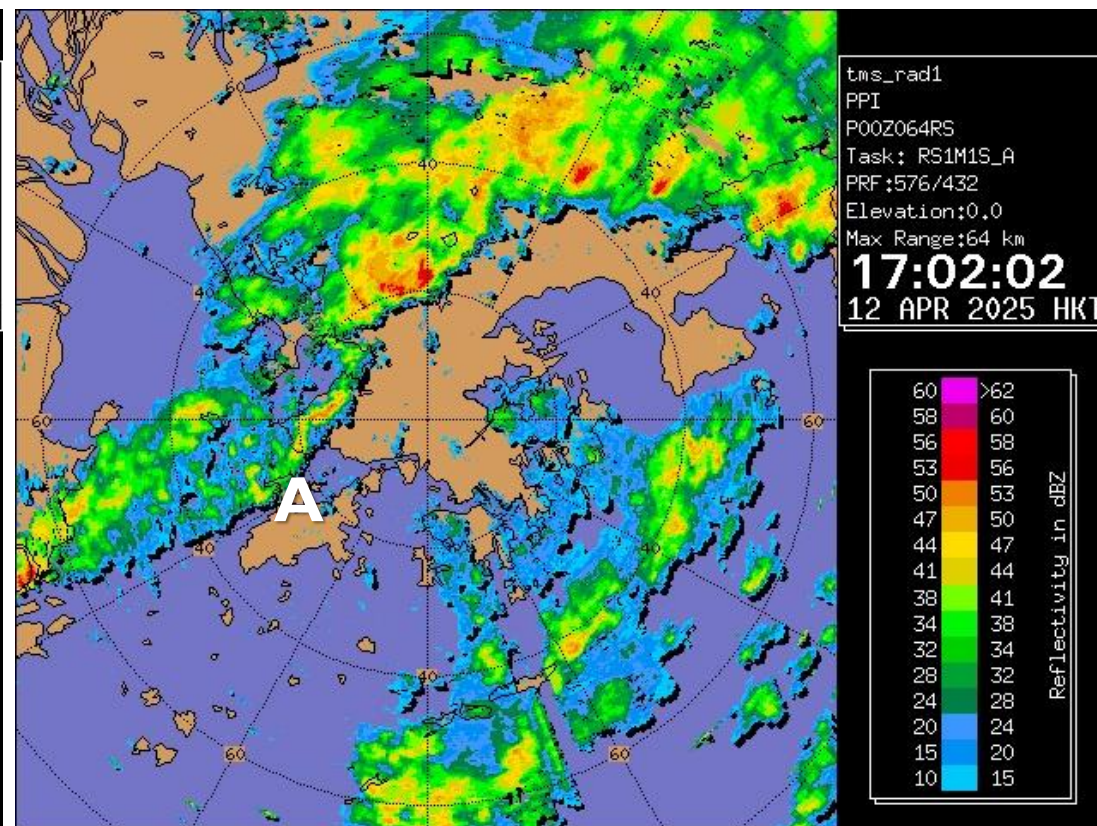
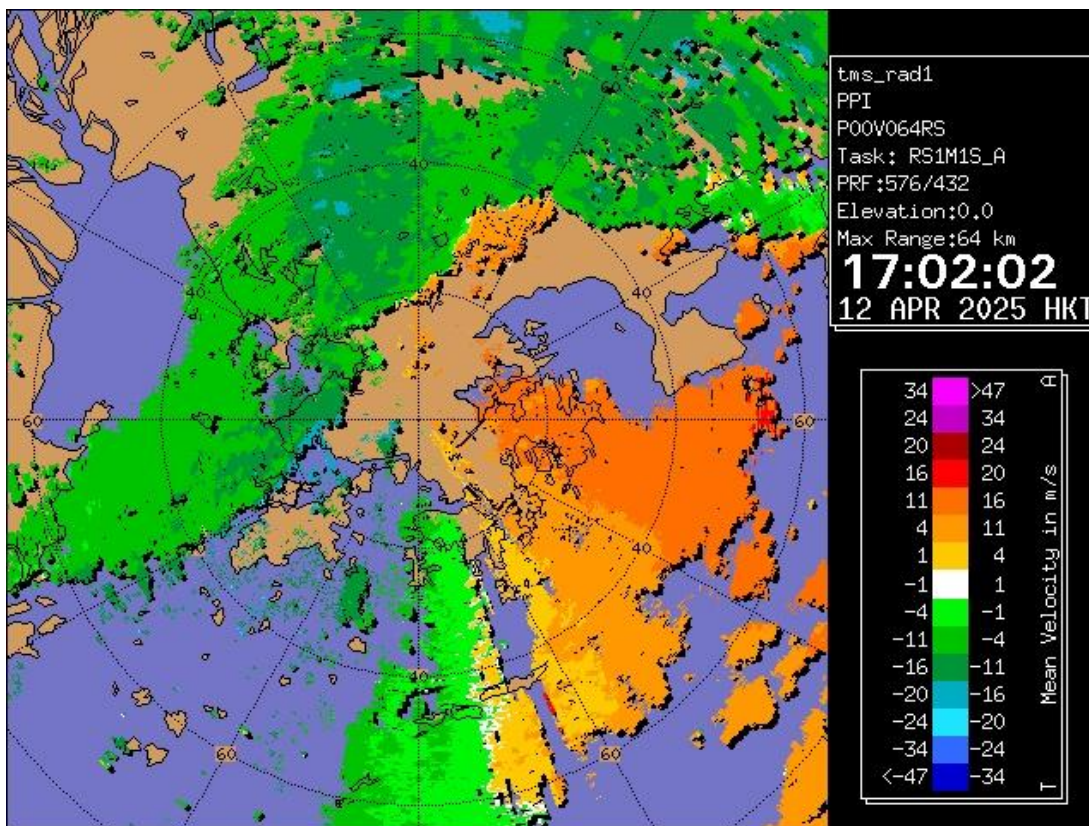


Storm	34		47
Gale	24		34
StrongF7	20		24
StrongF6	16		20
Fresh	11		16
Moderate	4		11
Light	1		4
Calm	-1		1
Light	-4		-1
Moderate	-11		-4
Fresh	-16		-11
StrongF6	-20		-16
StrongF7	-24		-20
Gale	-34		-24
Storm	-47		-34

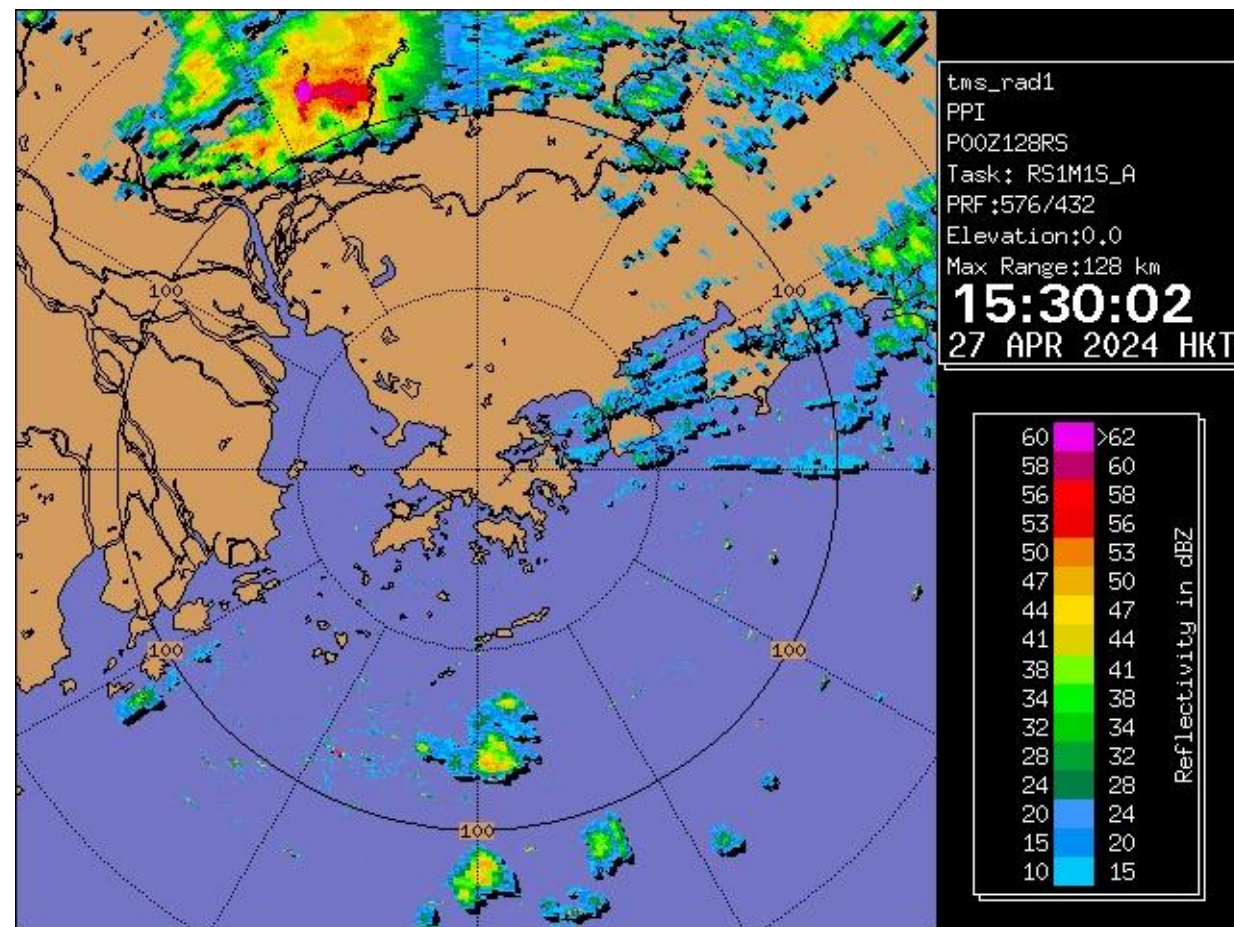
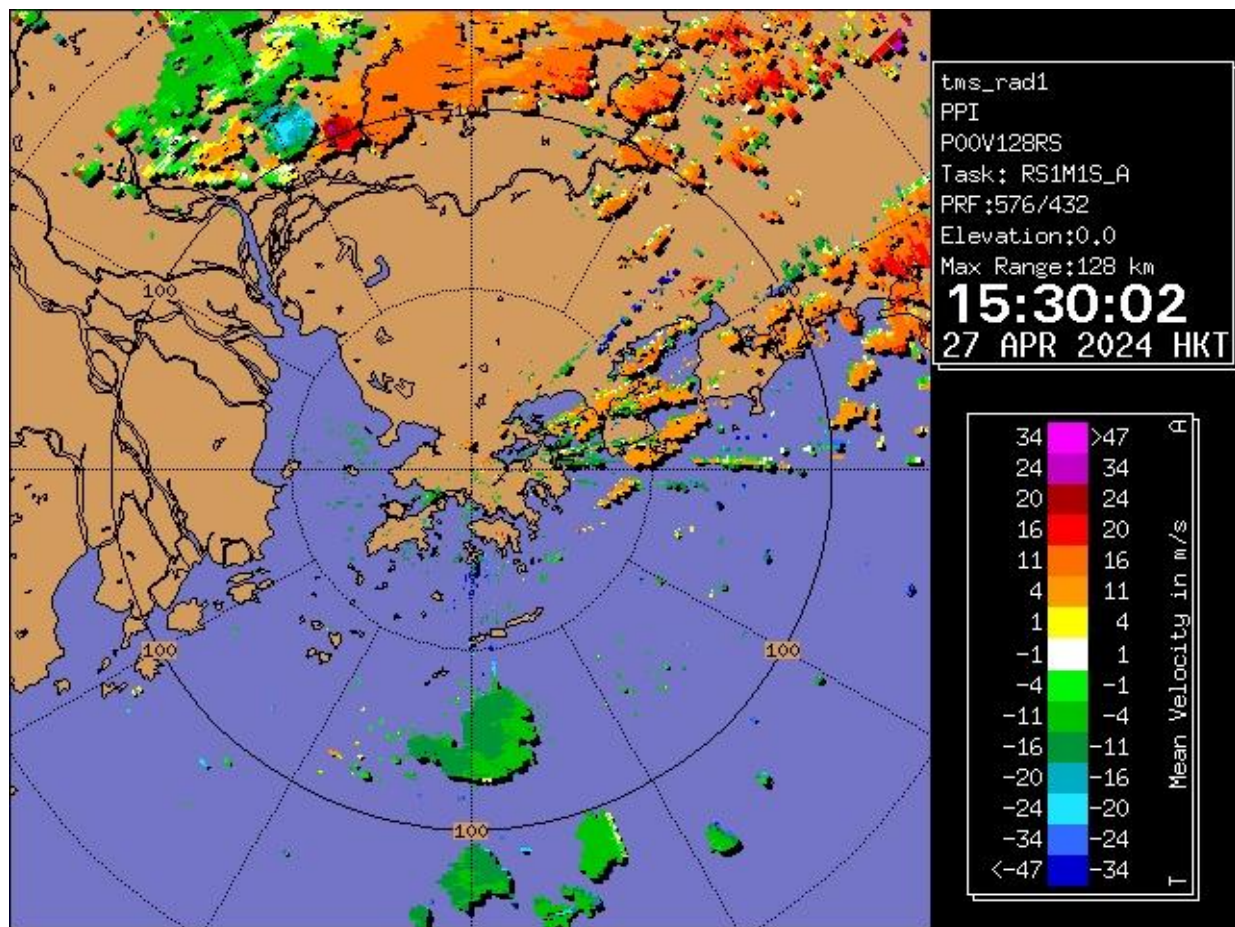
Beaufort Scale_0.7 Colour Scheme

Practical 2

- Identify the direction of wind flow and location of shear line from the radar images below
- Estimate the maximum wind (gust) recorded when the rain band pass over the vicinity of the HK International Airport (Point A)

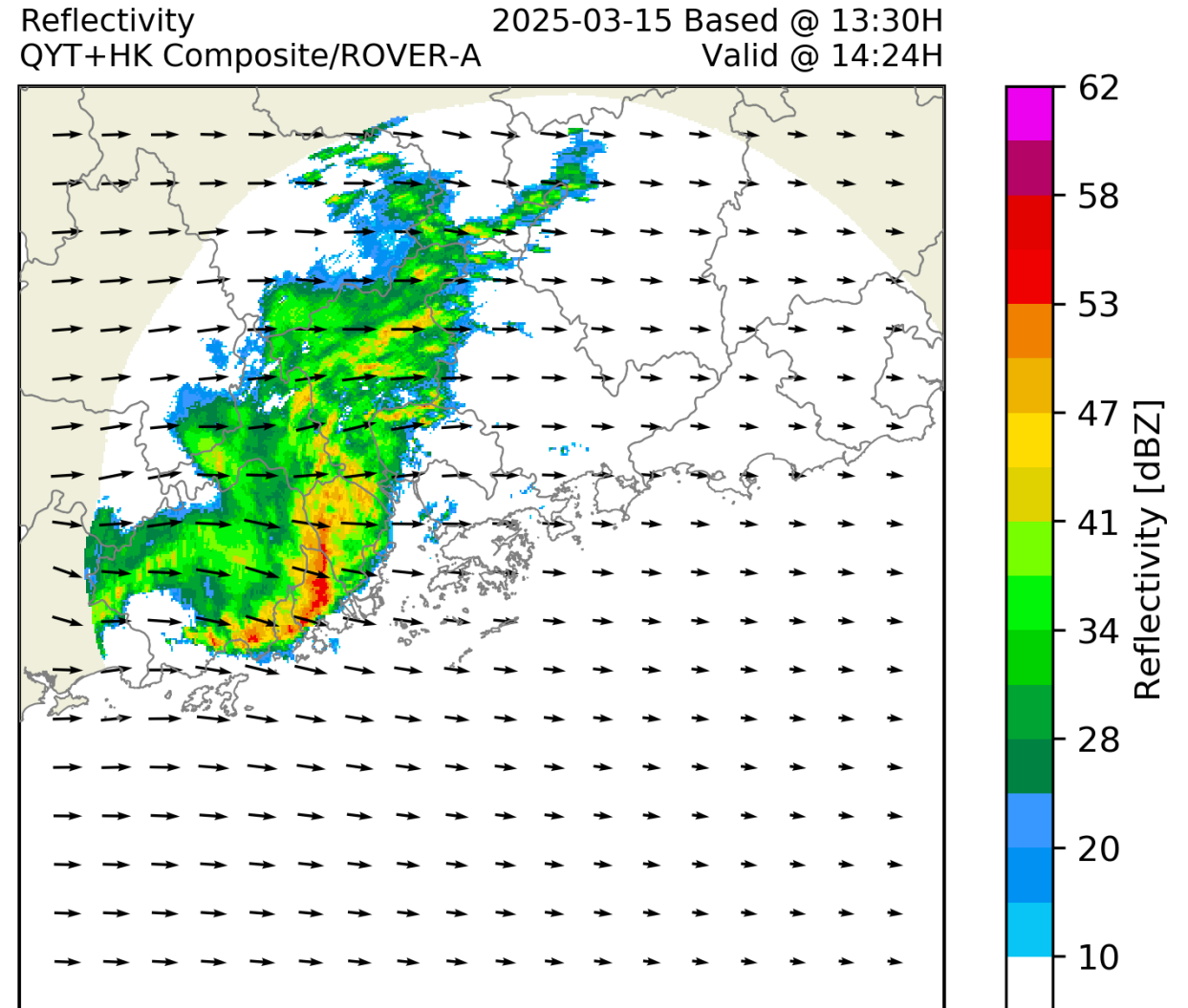


Can you identify any hazardous convective weather system from the following radar images?



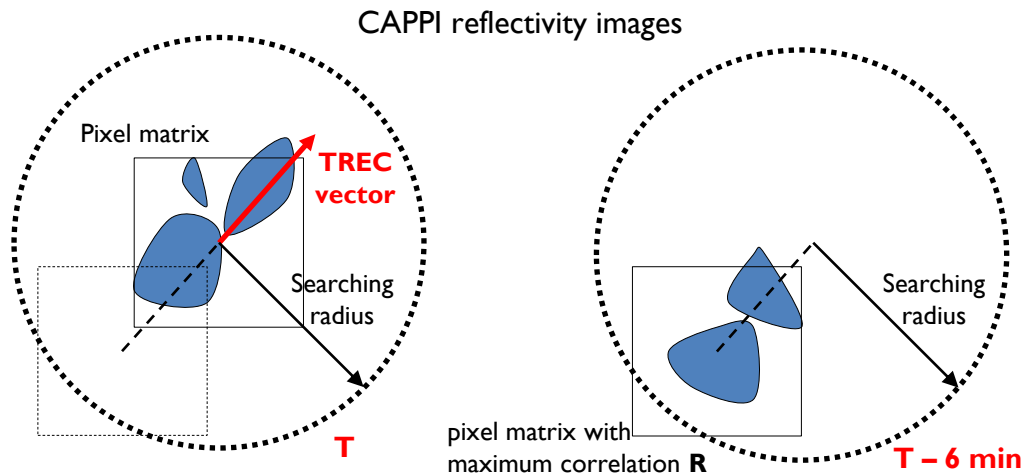
Nowcasting of Precipitation and Thunderstorms using Radar Image

- Determine the motion of radar echoes from successive radar images (e.g. every 6 minutes)
- Assume the intensity of echoes does not change, extrapolate radar echoes along the motion vectors and determine the future location of radar echoes in next 1-6 hours
- Derive forecast rainfall from forecast echo location
 - intensity (reflectivity) of radar echoes depending on size and number density of rain drops
- Limitation in radar extrapolation nowcast
 - no change in intensity
 - motion of echoes remains the same



QPF - tracking motion of radar echoes

Maximum Correlation



where Z_1 and Z_2 are the reflectivity at T+0 and T-6min respectively

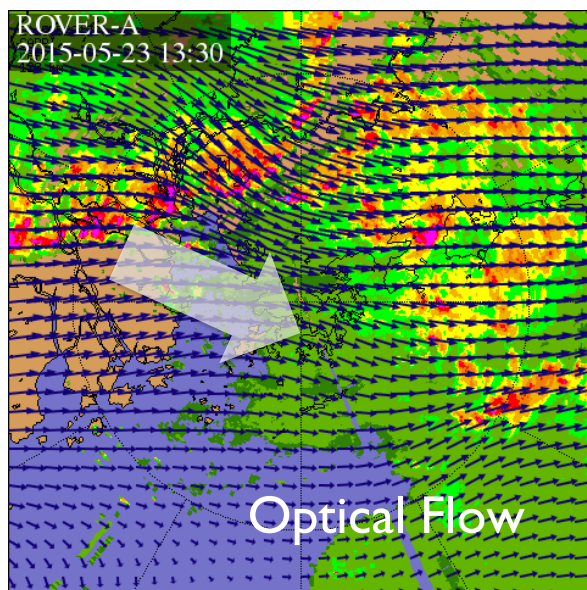
$$R = \frac{\sum_k Z_1(k) \times Z_2(k) - \frac{1}{N} \sum_k Z_1(k) \sum_k Z_2(k)}{\left[\left(\sum_k Z_1^2(k) - N \overline{Z_1}^2 \right) \times \left(\sum_k Z_2^2(k) - N \overline{Z_2}^2 \right) \right]^{1/2}}$$

Optical Flow

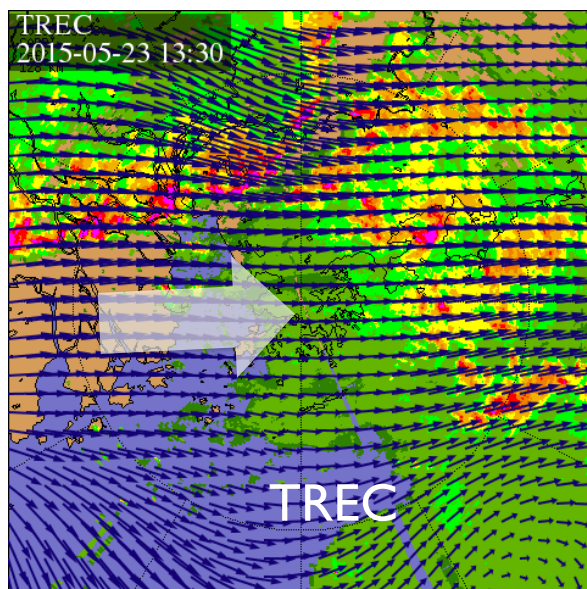
Given $I(x,y,t)$ the image brightness at point (x,y) at time t and the brightness is constant when pattern moves, the echo motion components $u(x,y)$ and $v(x,y)$ can be retrieved via **minimization of the cost function J**:

$$J = \iiint \left[\frac{\partial I}{\partial t} + u \frac{\partial I}{\partial x} + v \frac{\partial I}{\partial y} \right]^2 dx dy dt$$

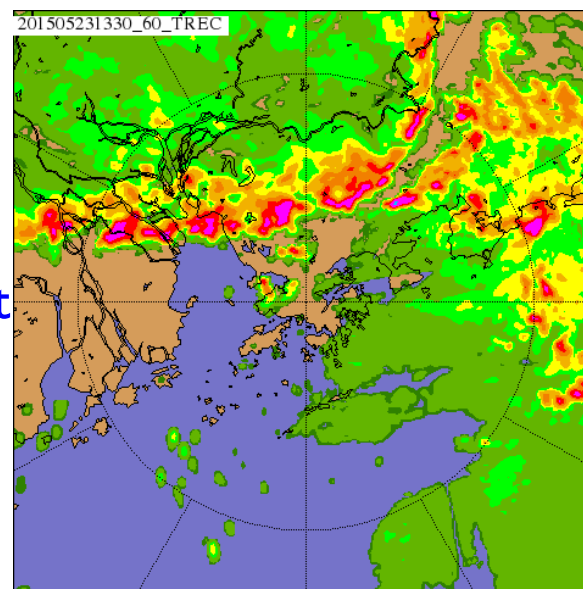
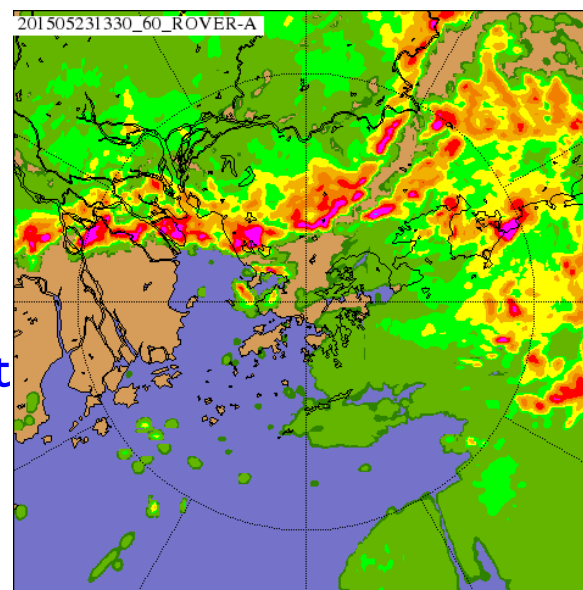
1-hr nowcast reflectivity using optical flow versus TREC motion fields



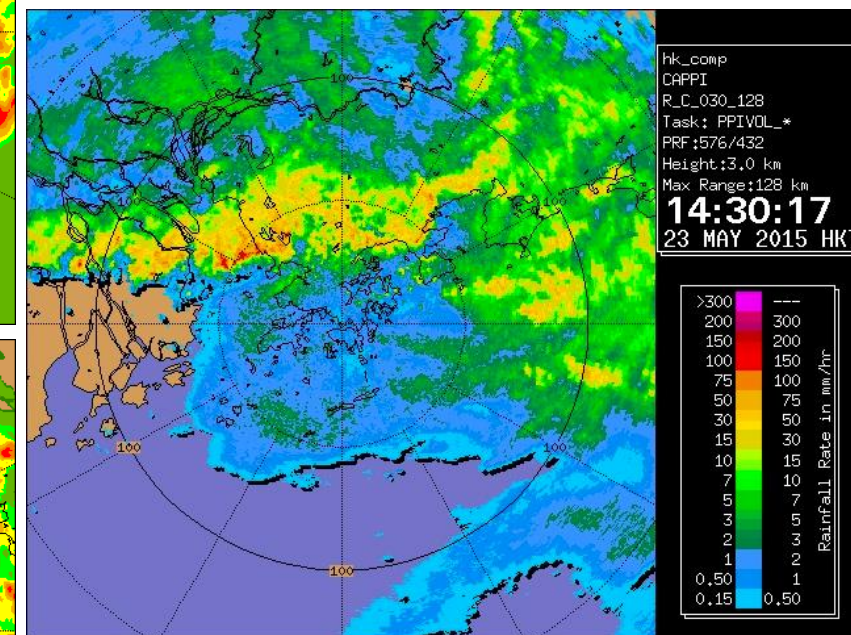
1-hr
Nowcast



1-hr
Nowcast



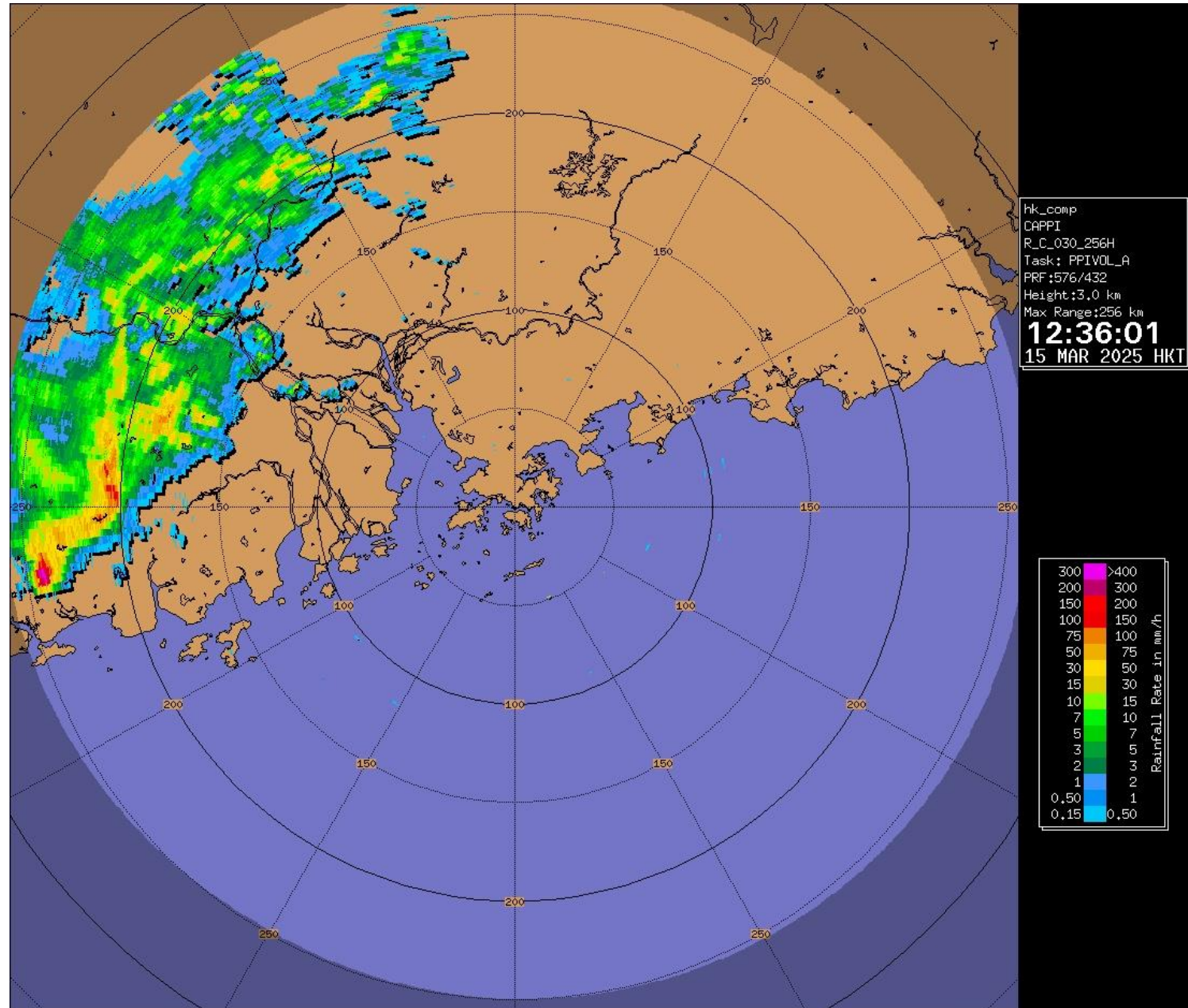
Actual



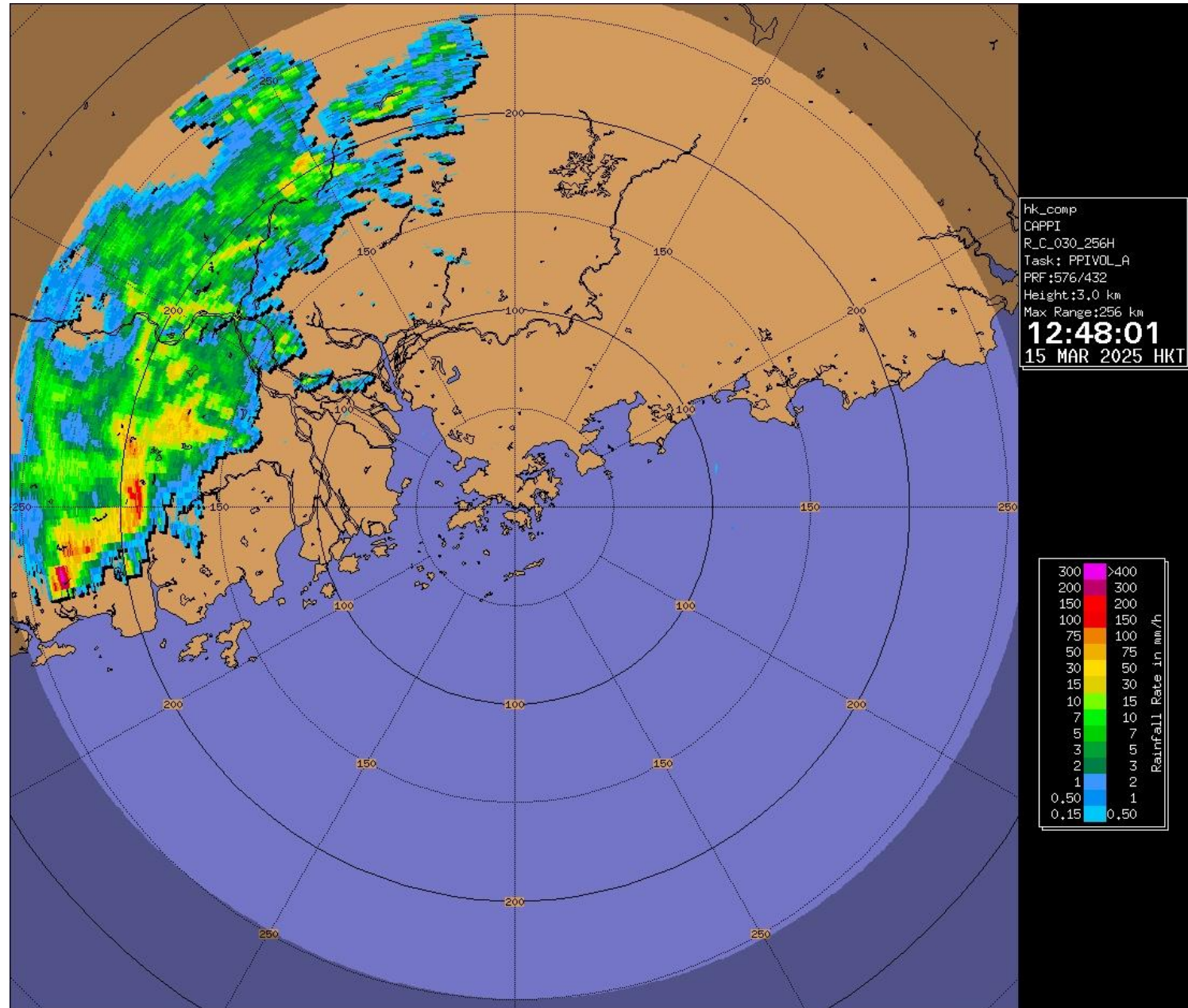
Given the following sequence of radar image, estimate:

- (a) Moving speed of intense rainband (i.e. front-edge of yellowish radar echo areas) over the western coastal areas of Guangdong
- (b) When would it start to affect Hong Kong?

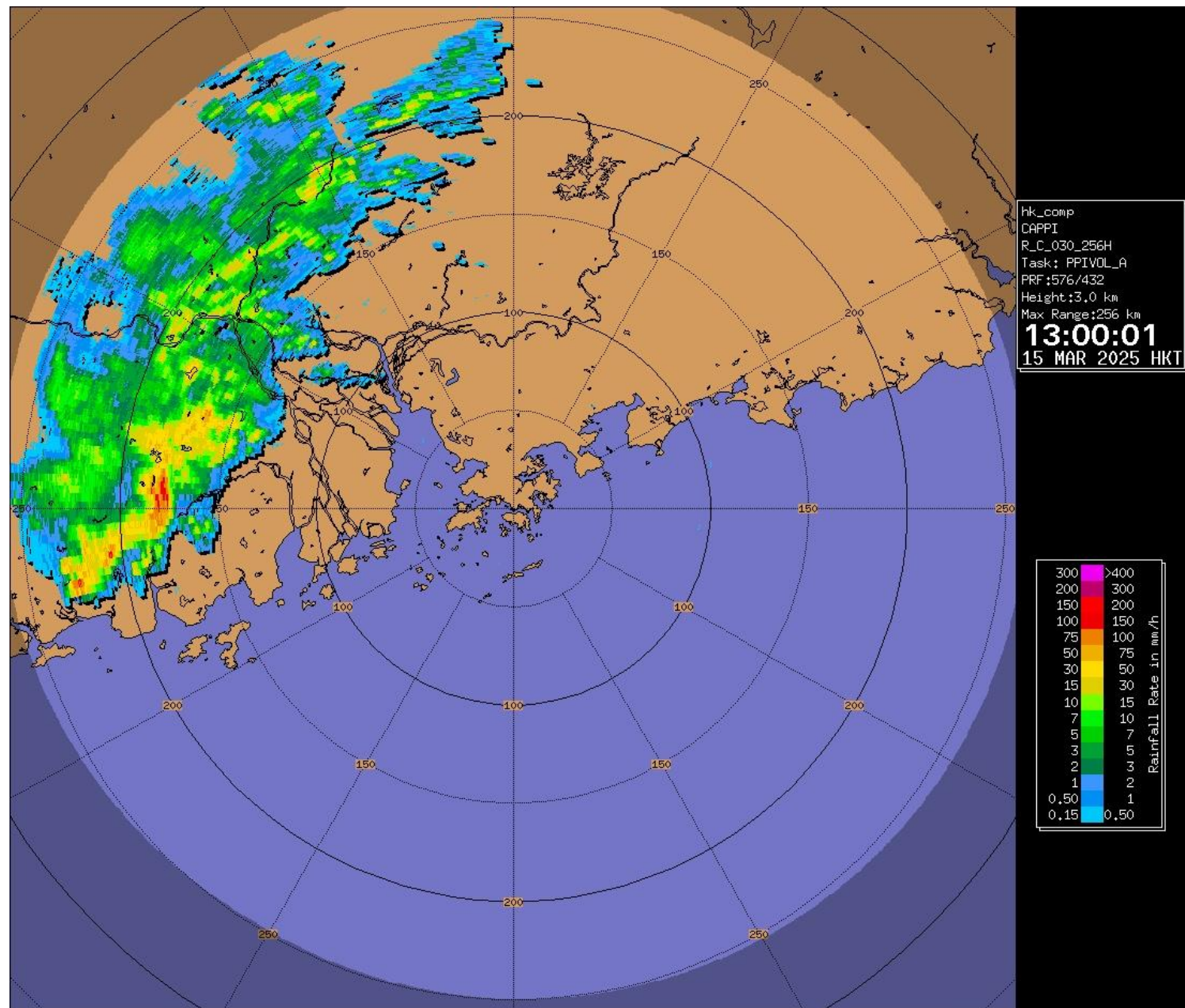
Practical 3



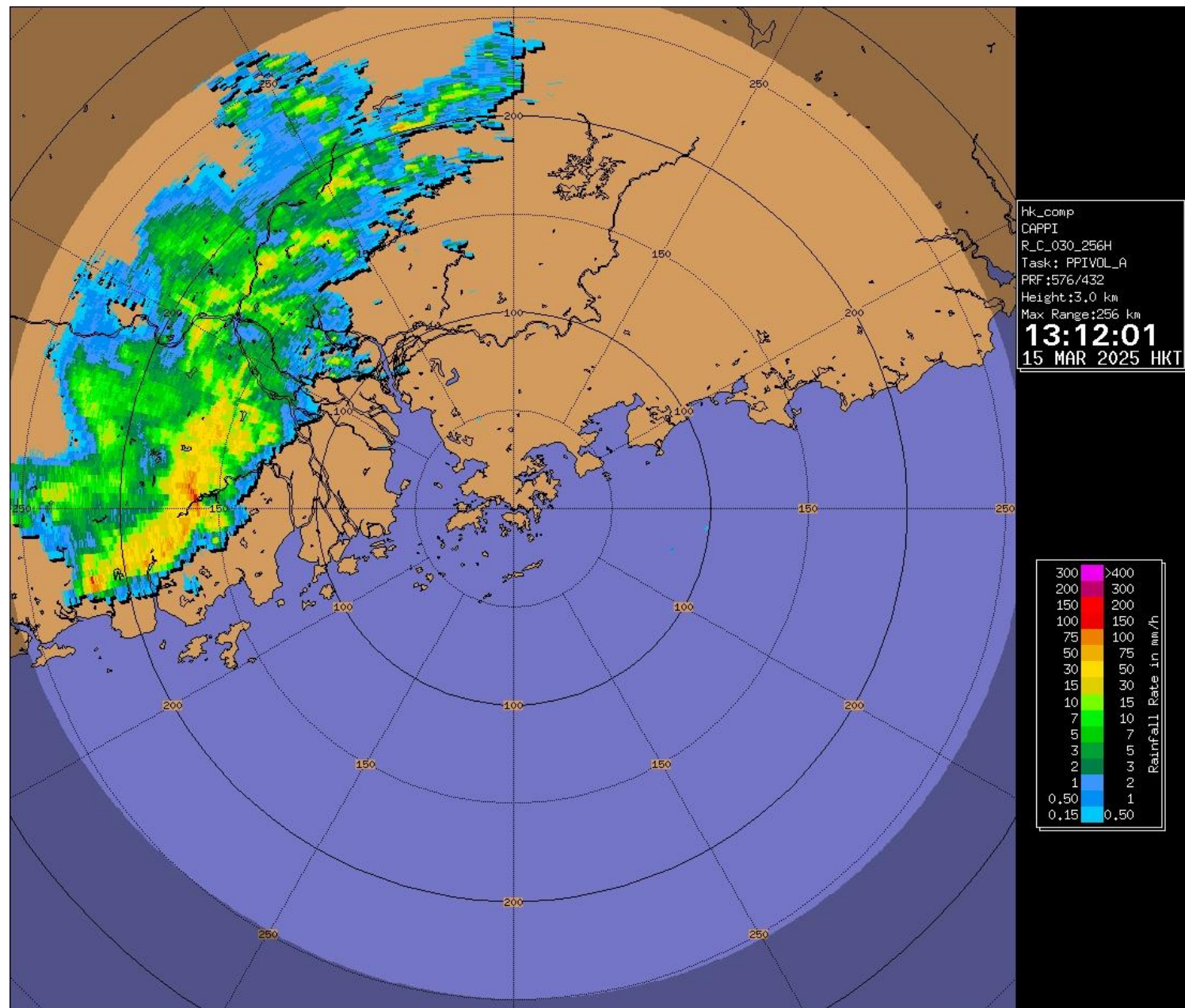
Practical 3



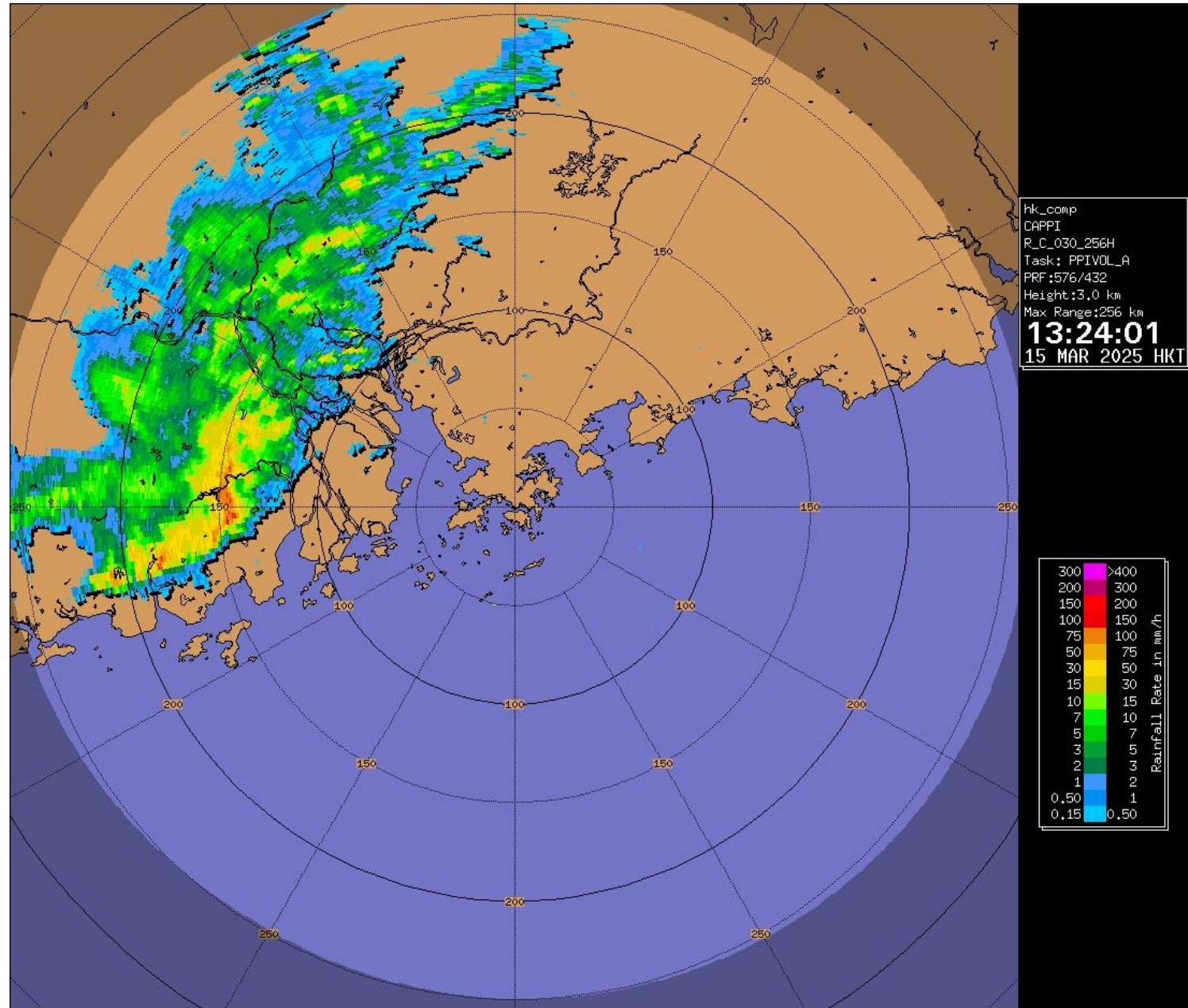
Practical 3



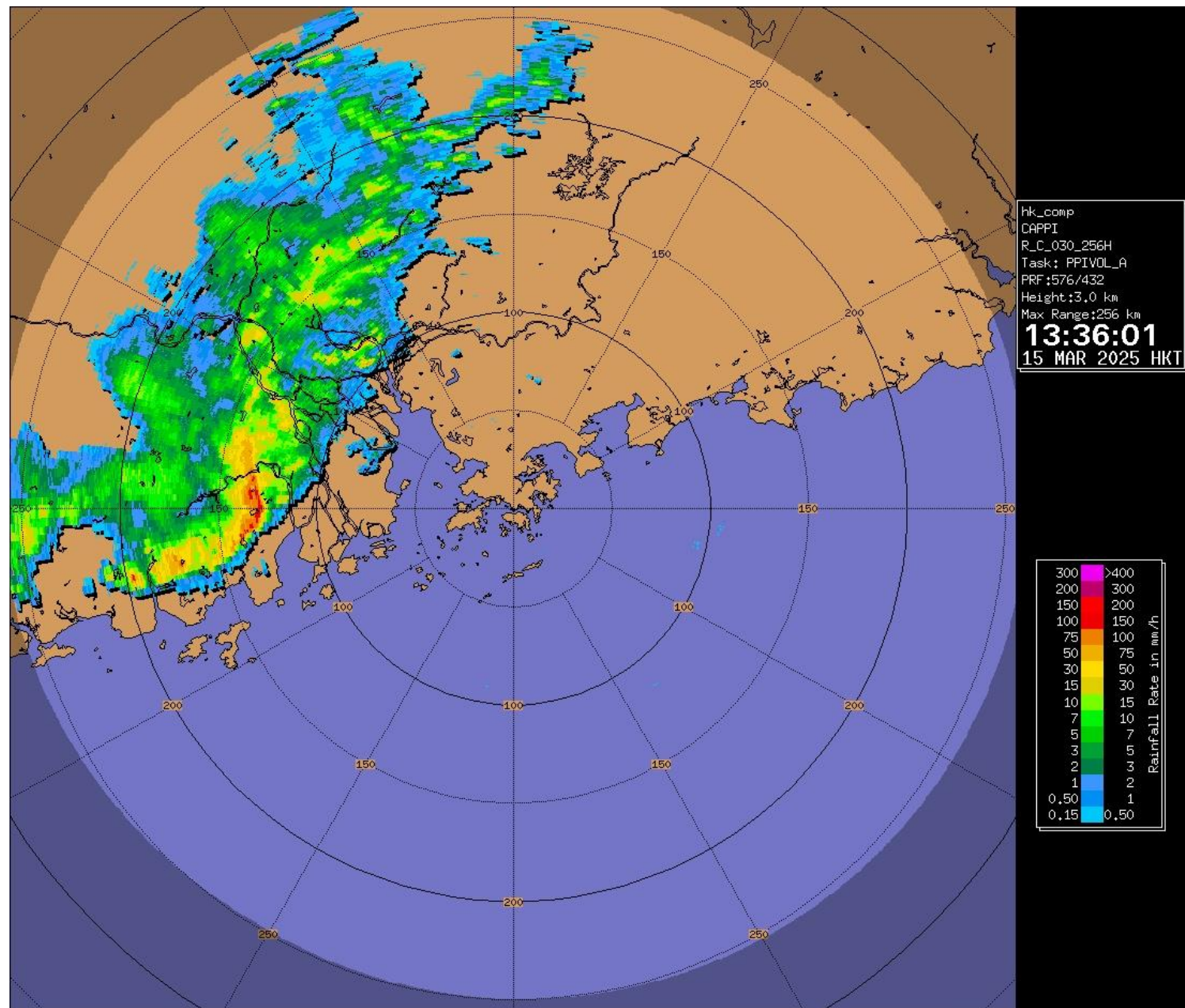
Practical 3



Practical 3



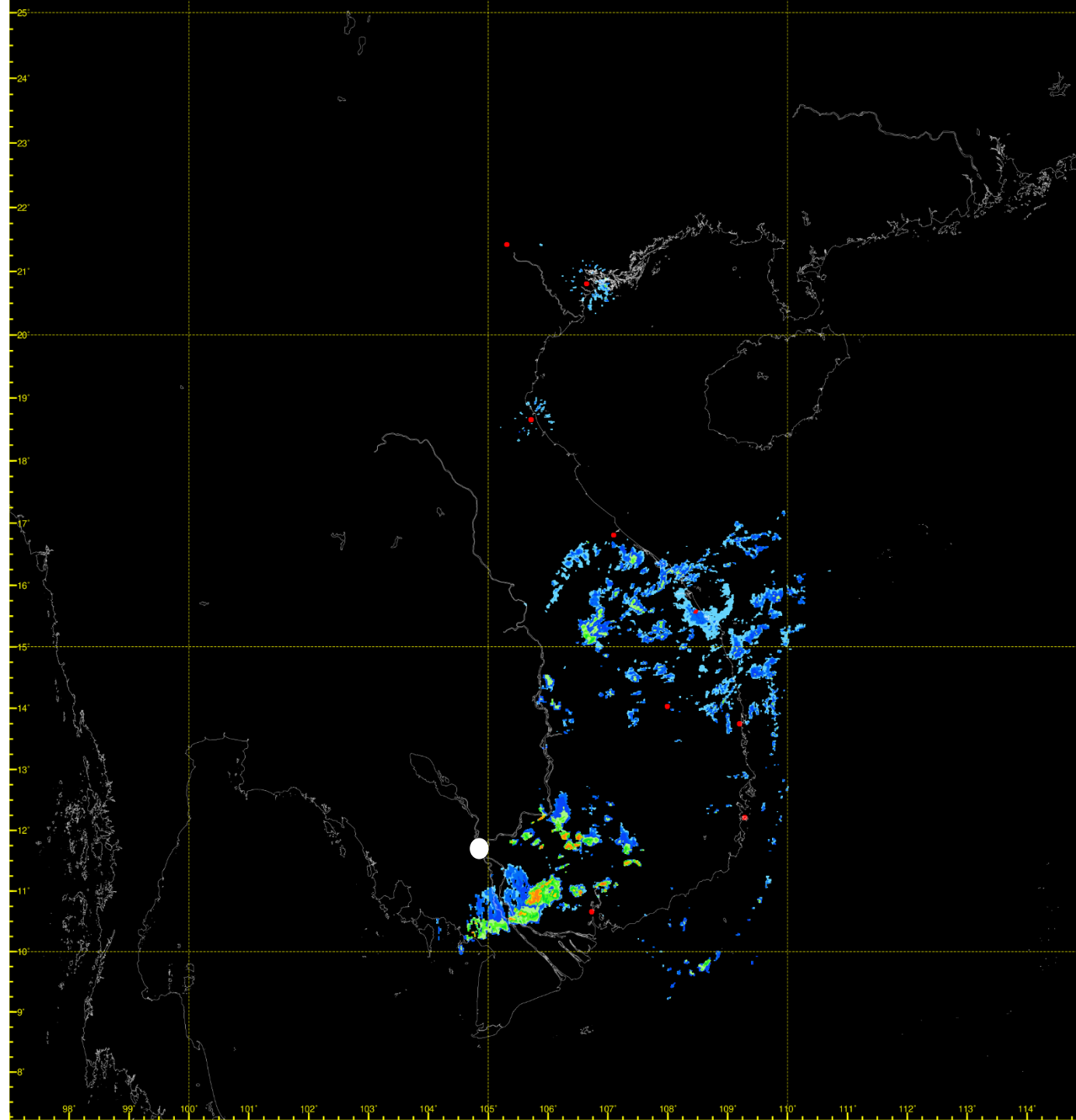
Practical 3



Practical 4

2025-03-10

10:30 UTC



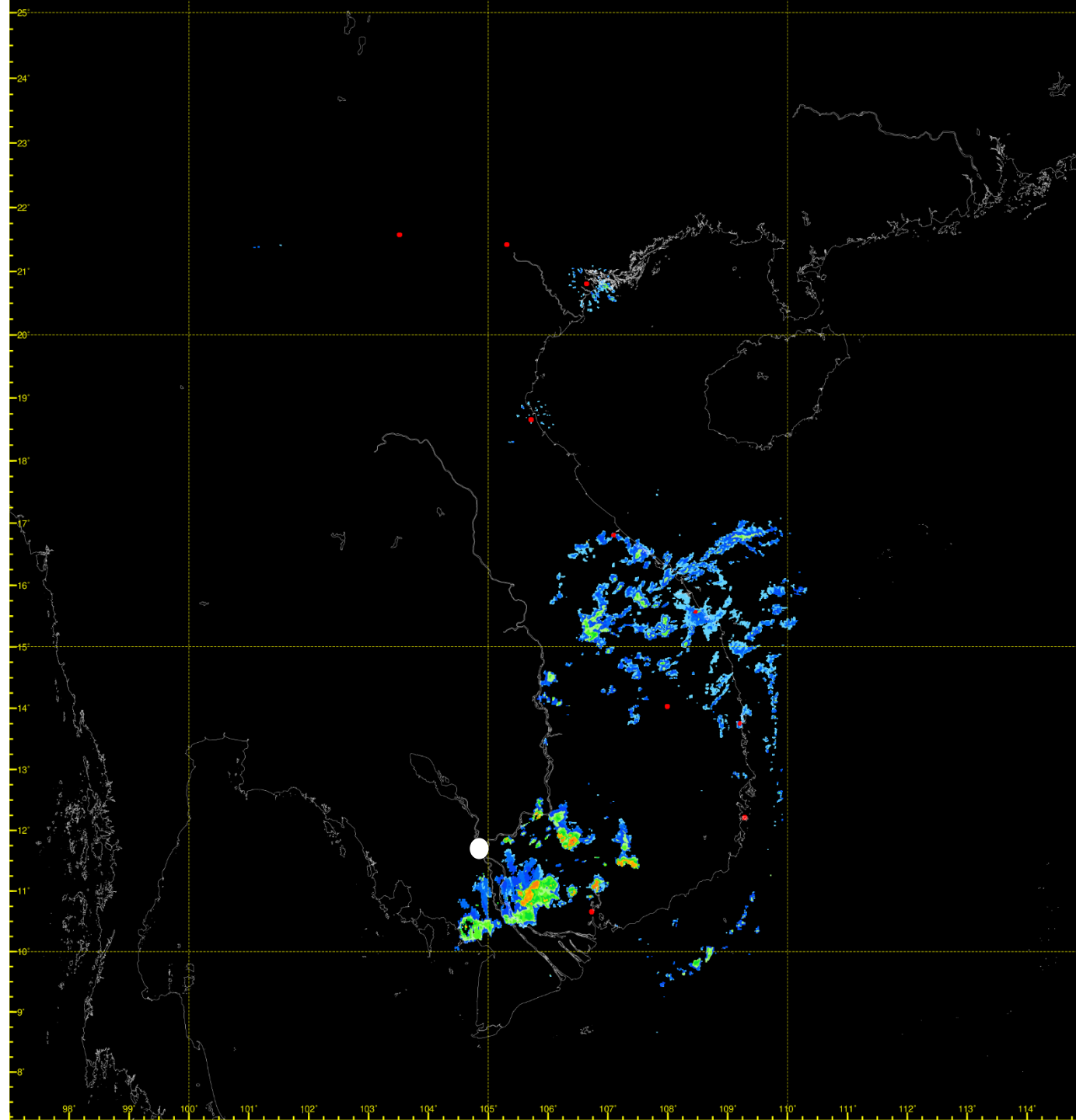
When would it
expect to affect
Phnom Penh?

11.41N 104.89E

Practical 4

2025-03-10

11:00 UTC



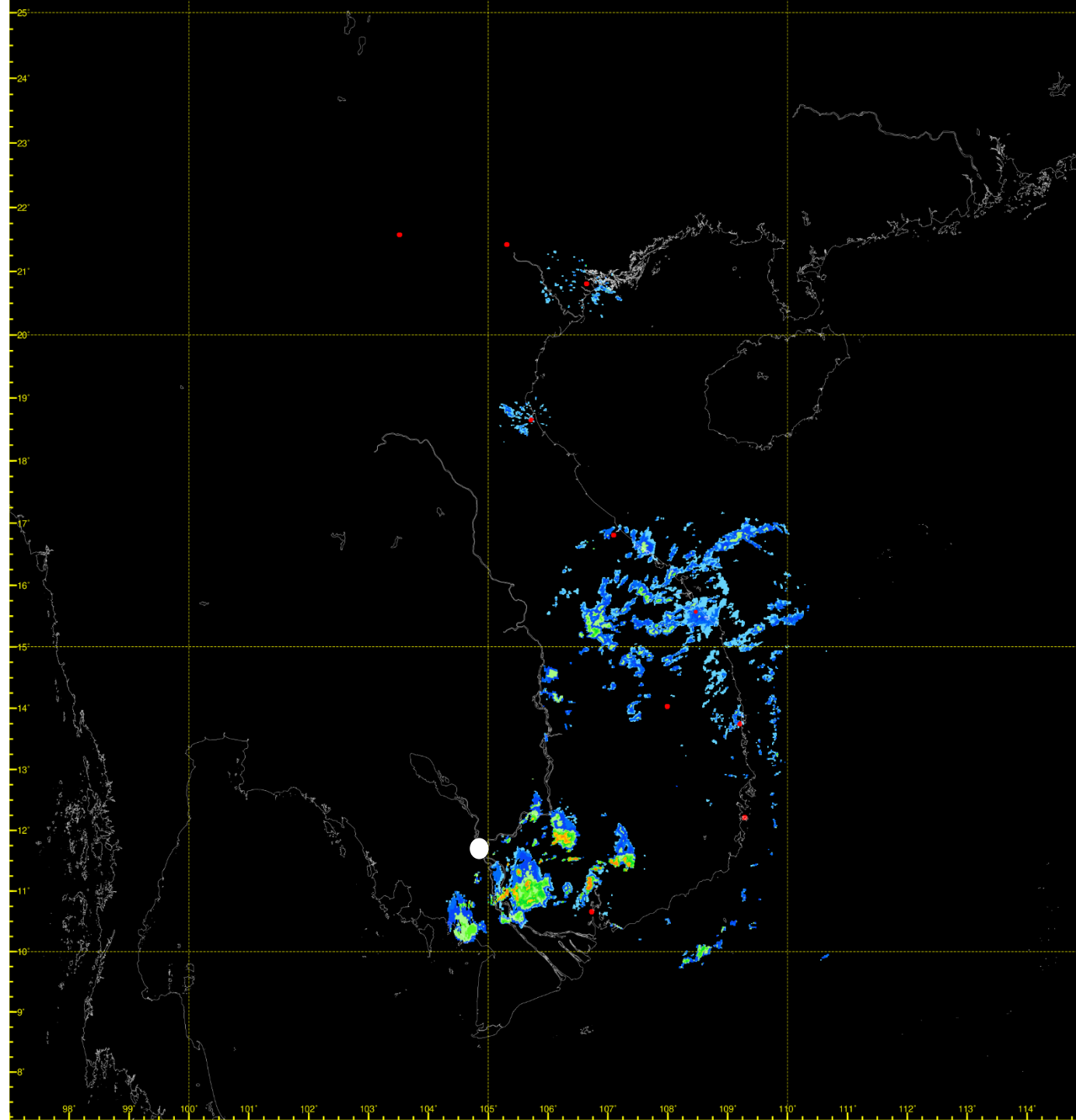
When would it
expect to affect
Phnom Penh?

11.41N 104.89E

Practical 4

2025-03-10

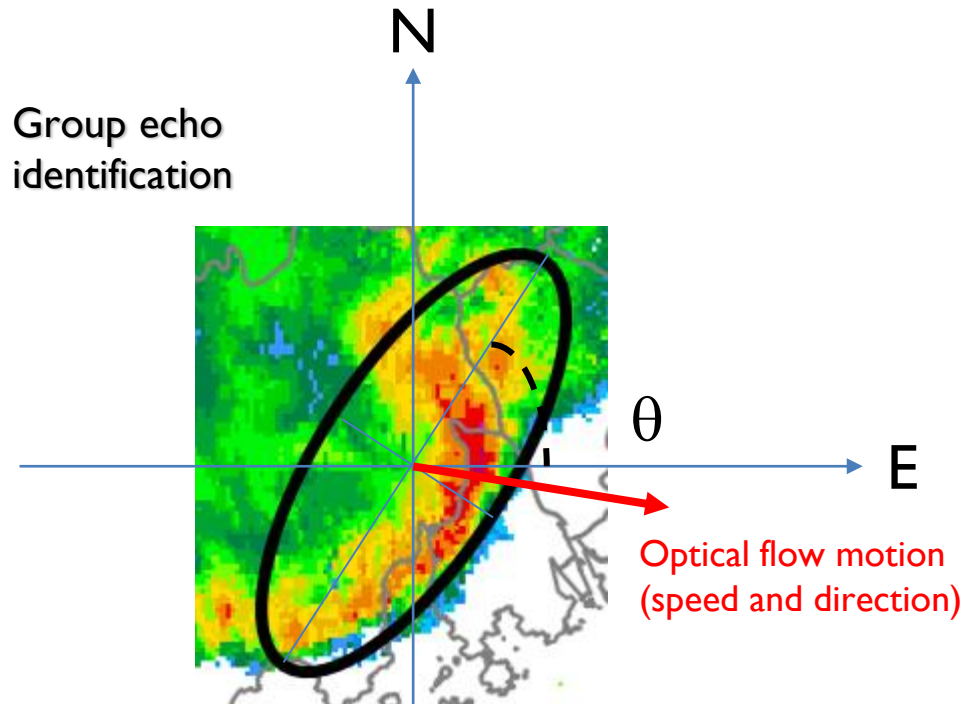
11:30 UTC



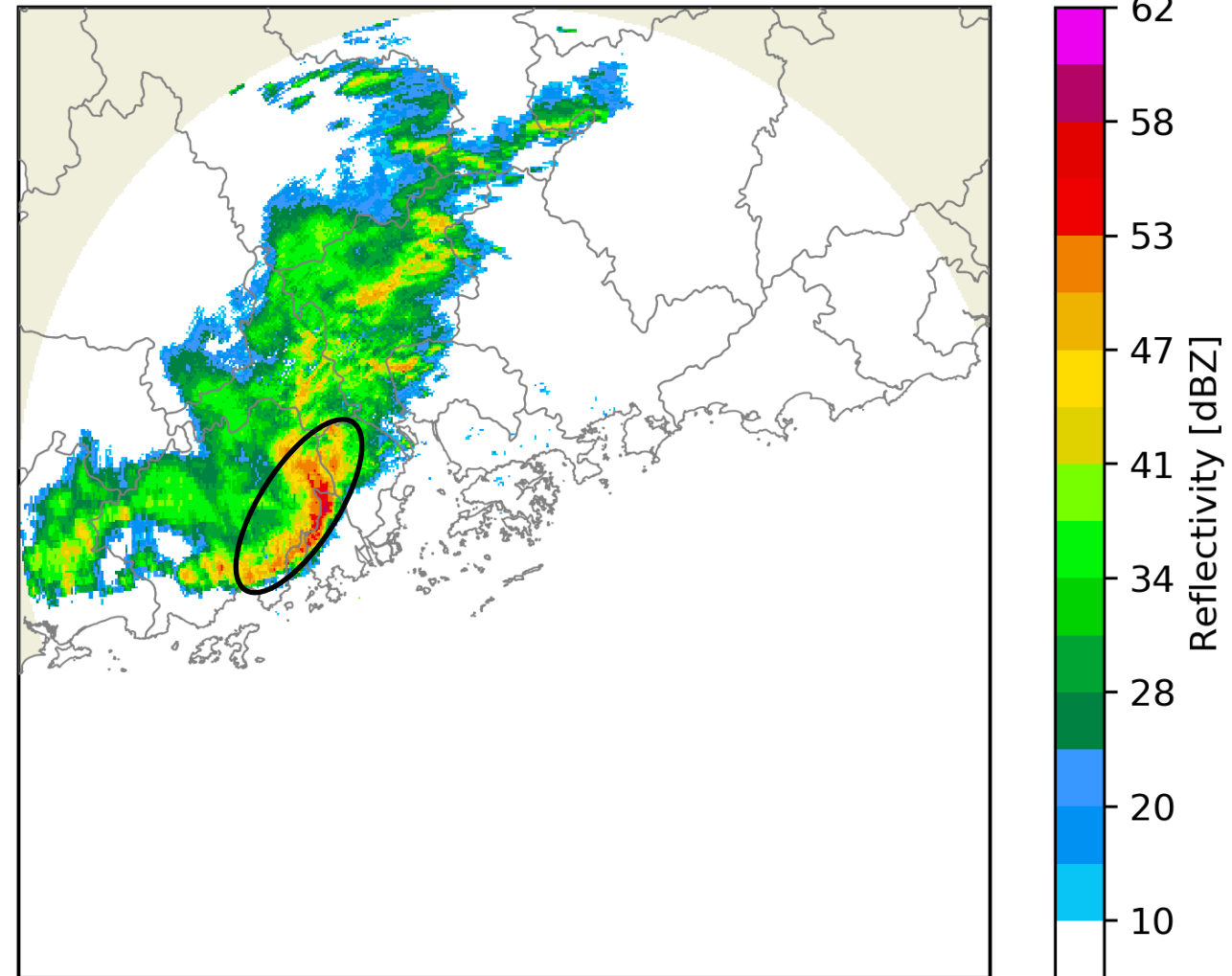
When would it
expect to affect
Phnom Penh?

11.41N 104.89E

Tracking of Severe Weather Objects in SWIRLS

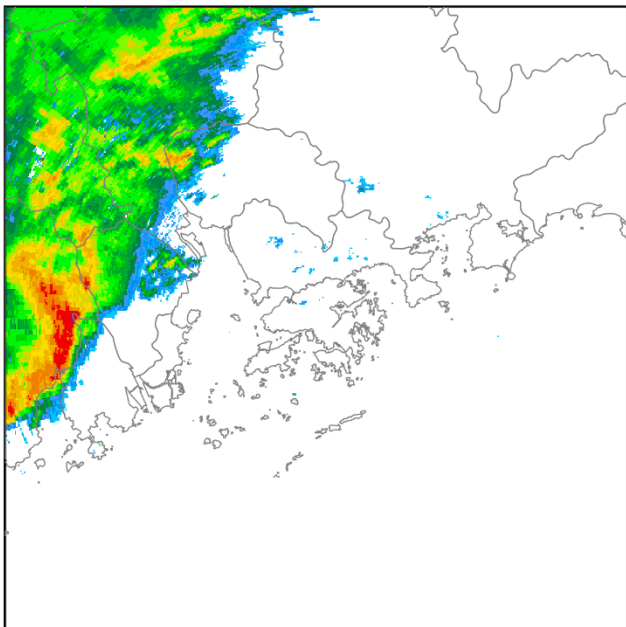


- Fitting elliptical object based on selected reflectivity thresholds on single and multi-layer CAPPI.
- Determine intensity weighted centroid (centre of ellipse) and geometric (principal component) parameters including major axis, minor axis and orientation angle (θ)
- Specify the storm object properties for tracking and identifying severe weather characteristics: hail signature, gust, lightning and rainfall intensities



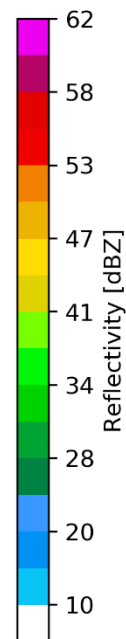
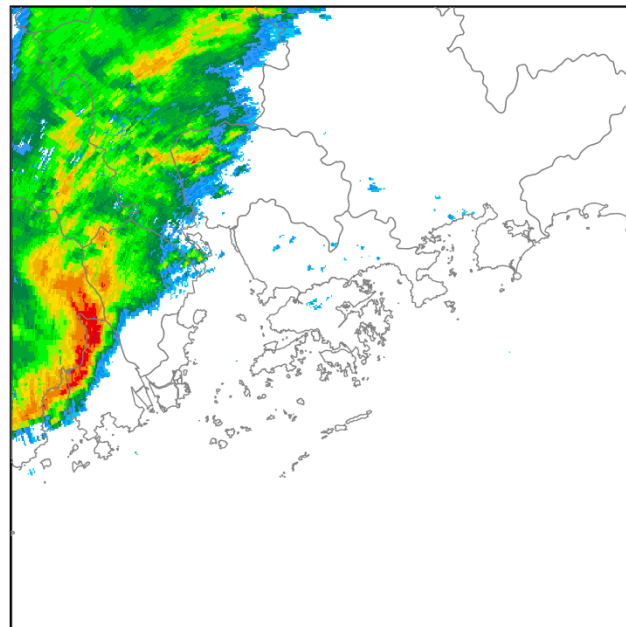
2-km HK Composite CAPPI
Based @ 2025-03-15 13:54H

Range= 128 km

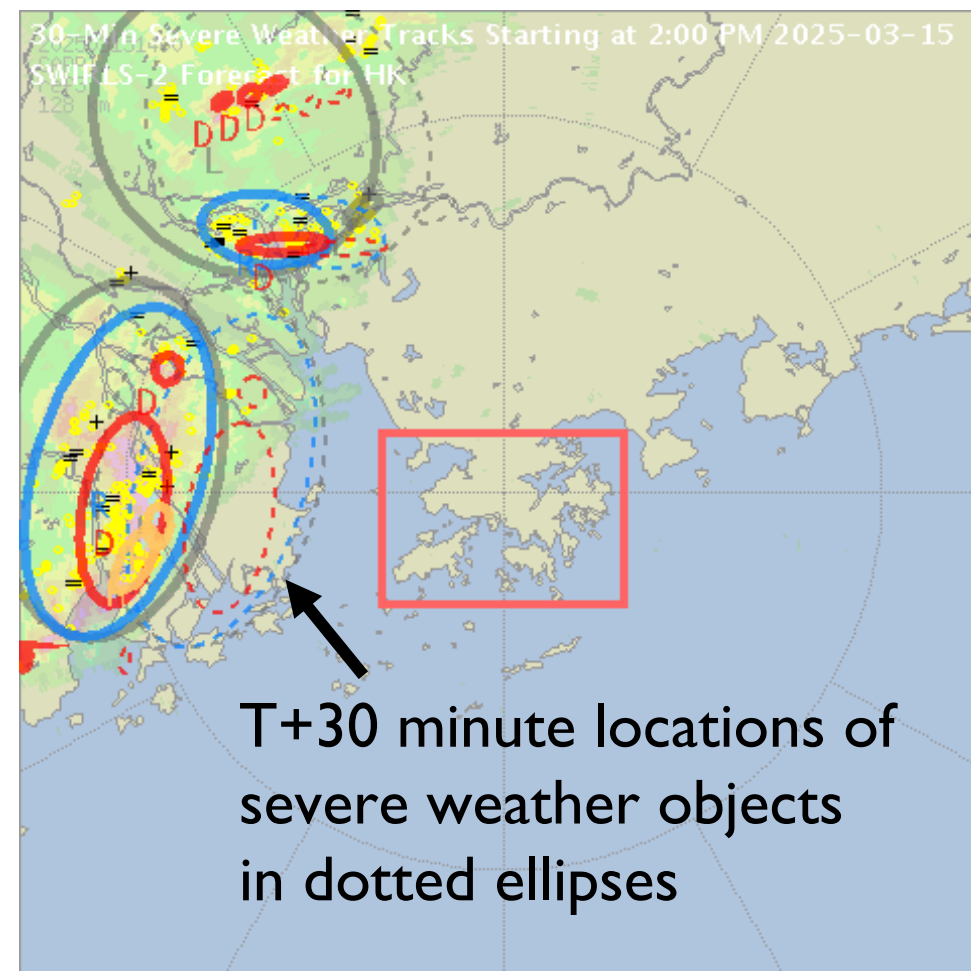
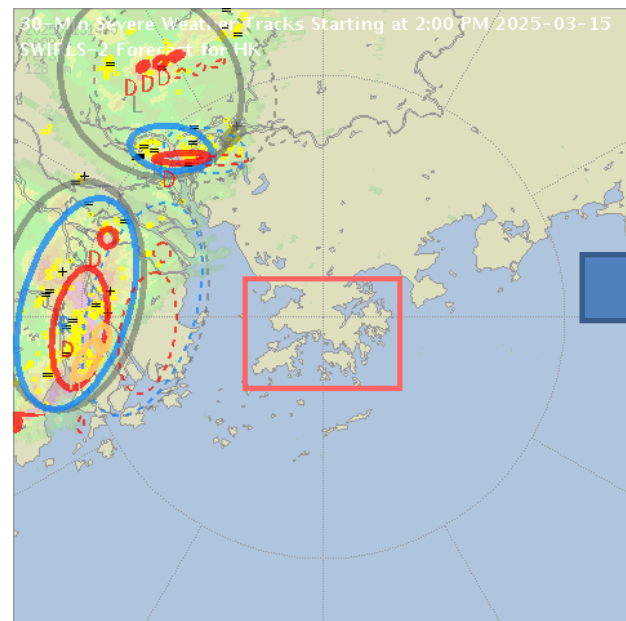
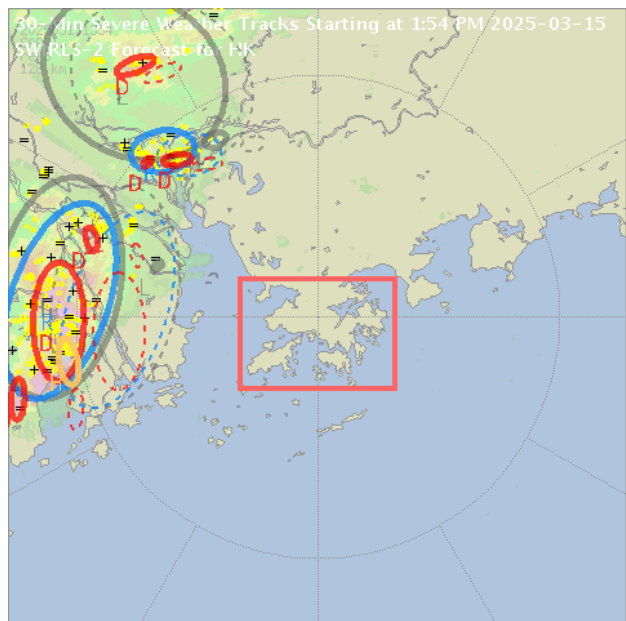


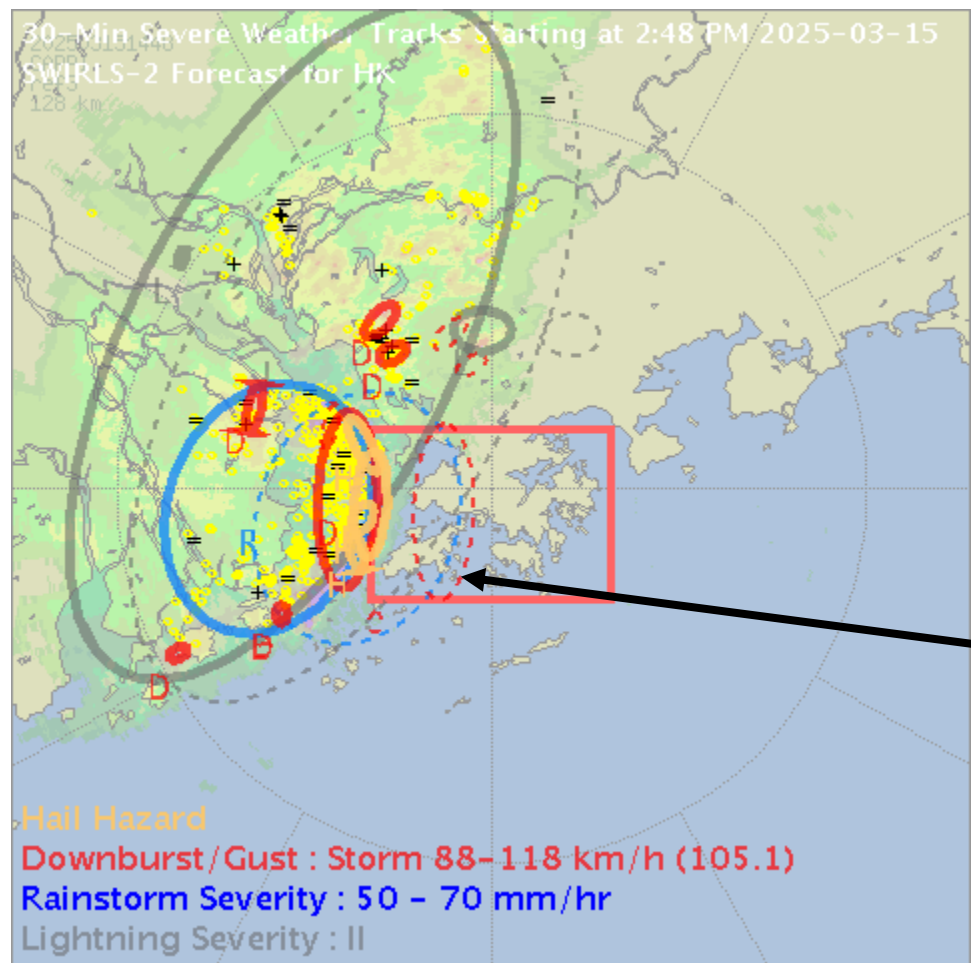
2-km HK Composite CAPPI
Based @ 2025-03-15 14:00H

Range= 128 km

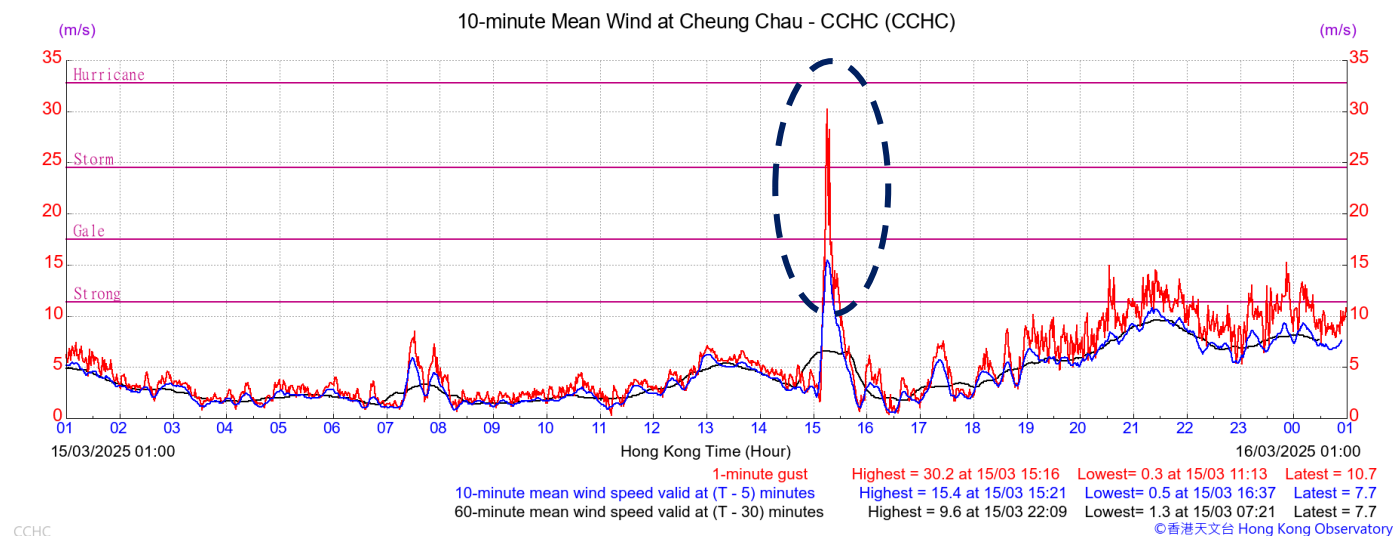


Tracking Severe Weather Objects in Radar Imagery and Nowcast

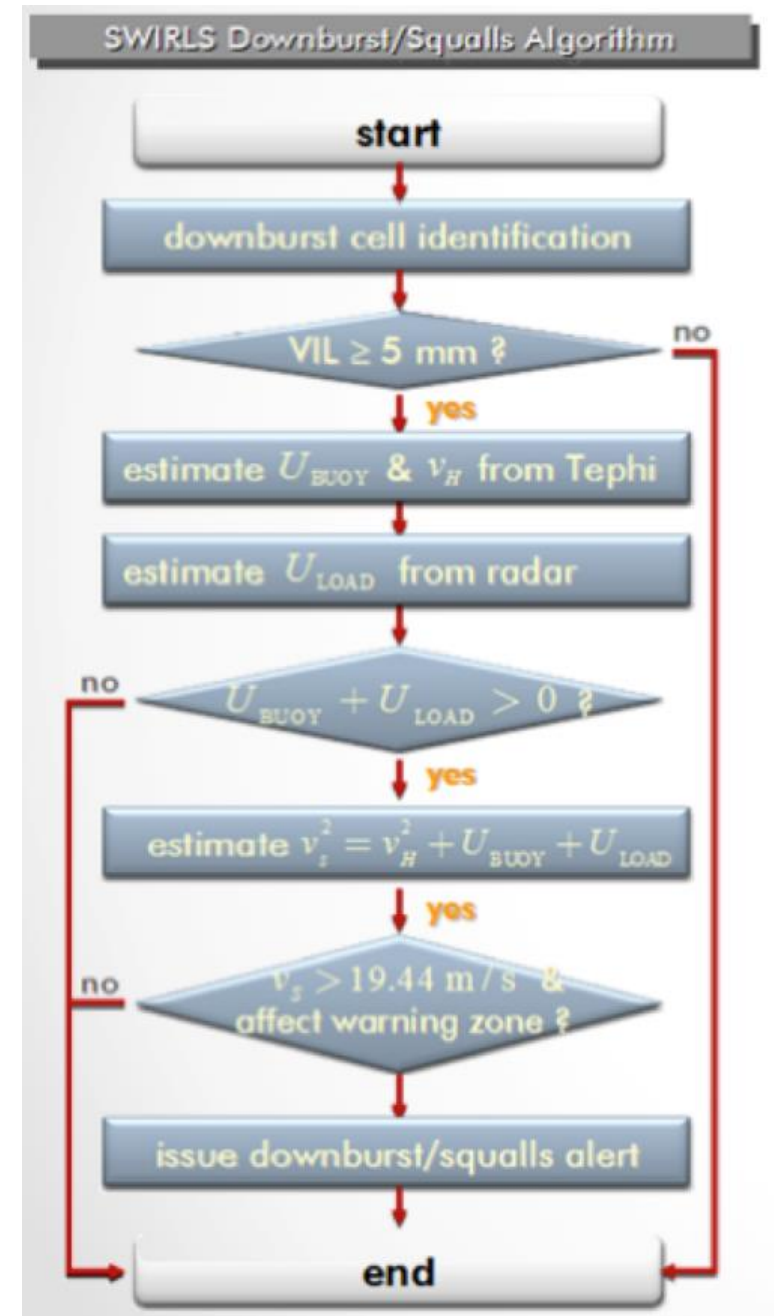
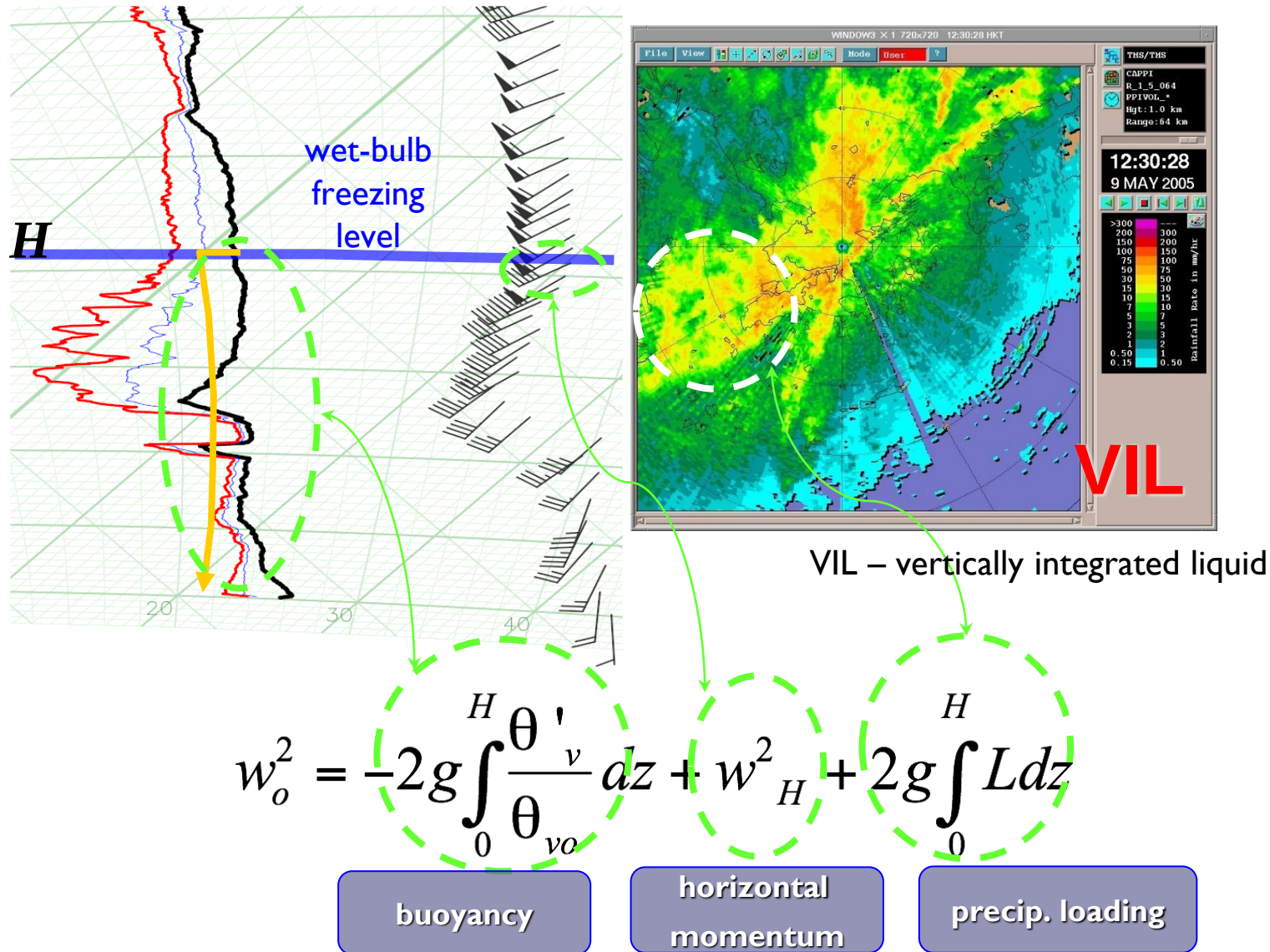




High-impact hazards of **hail**, **violent gust** / **convective downburst**, significant lightning and **heavy rain** within the next 30 minutes in Hong Kong area (red box)



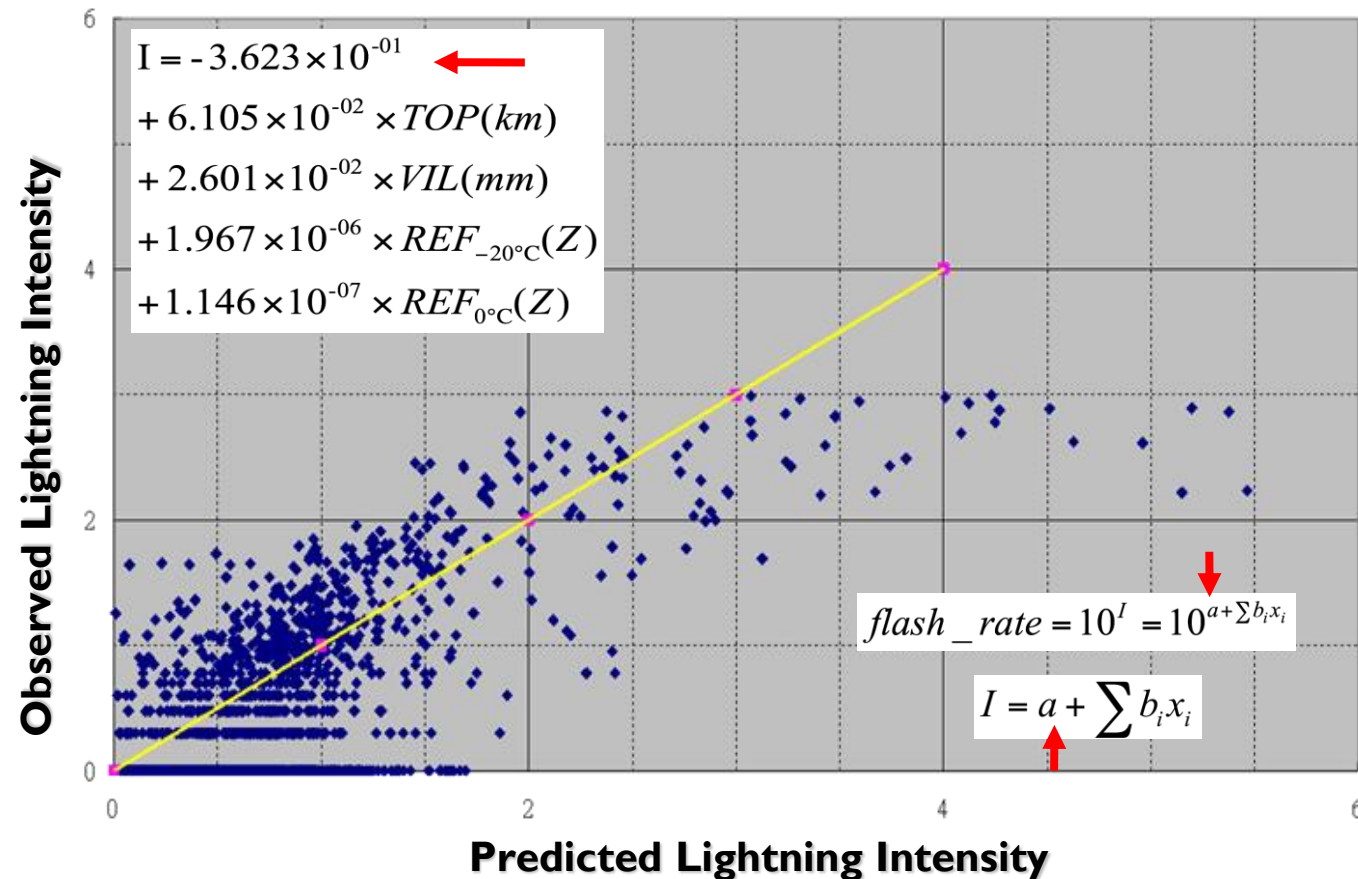
SWIRLS Downburst Nowcast Algorithm



Indicators of the cloud-to-ground (C-G) lightning onset

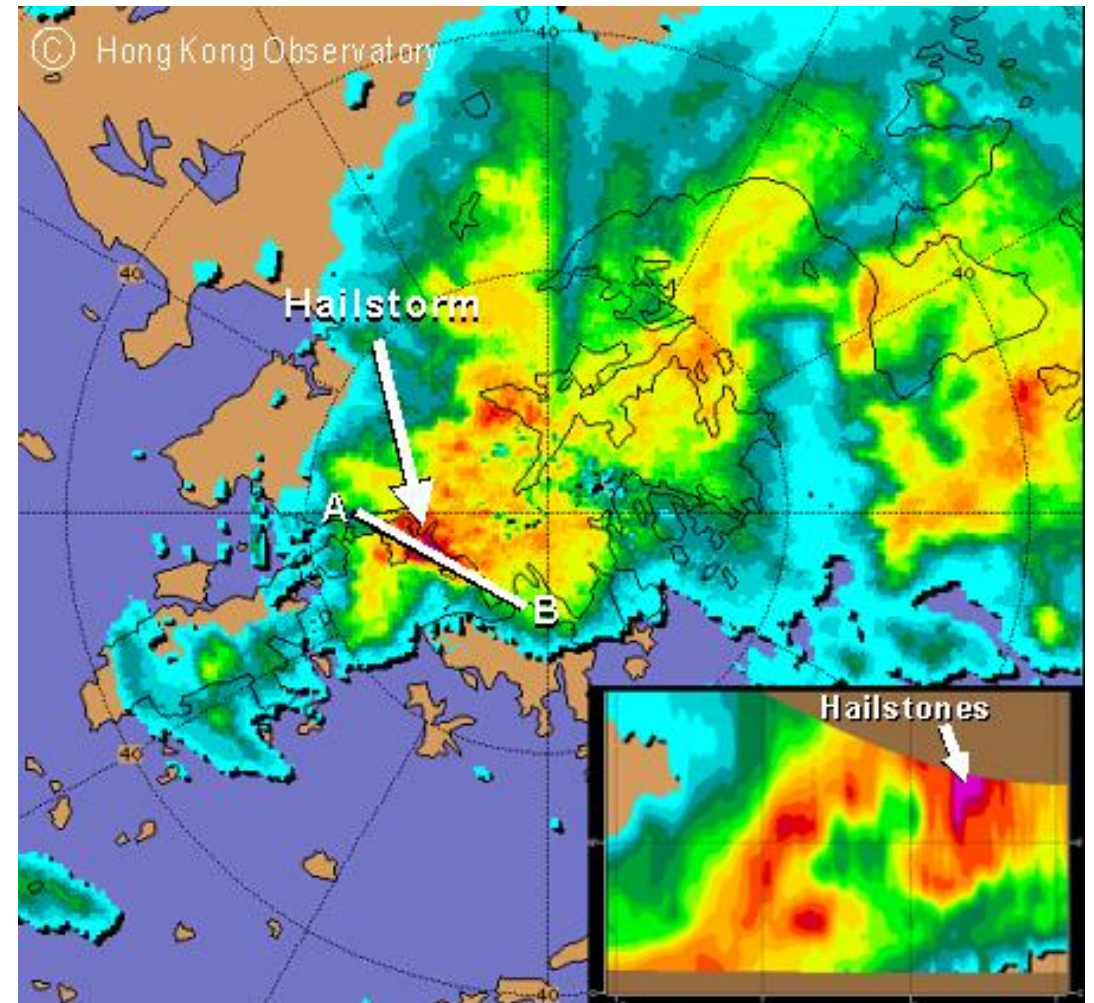
- effective indicators in predicting onset of C-G lightning in 10-20 minutes:

- TOP > 7 km
- VIL > 5 mm
- $REF_{0^{\circ}C} > 42$ dBZ
- $REF_{-10^{\circ}C} > 17$ dBZ
- $REF_{-20^{\circ}C} > 0$ dBZ

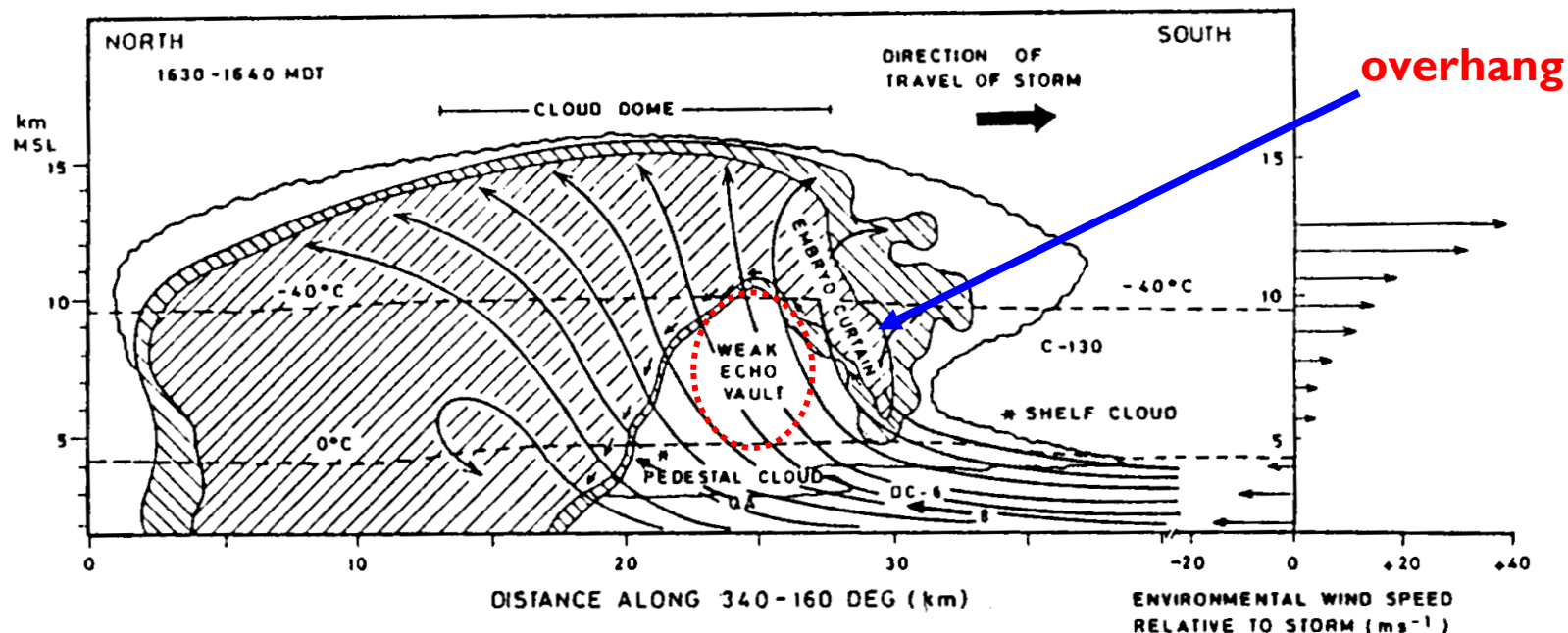


Hail Detection

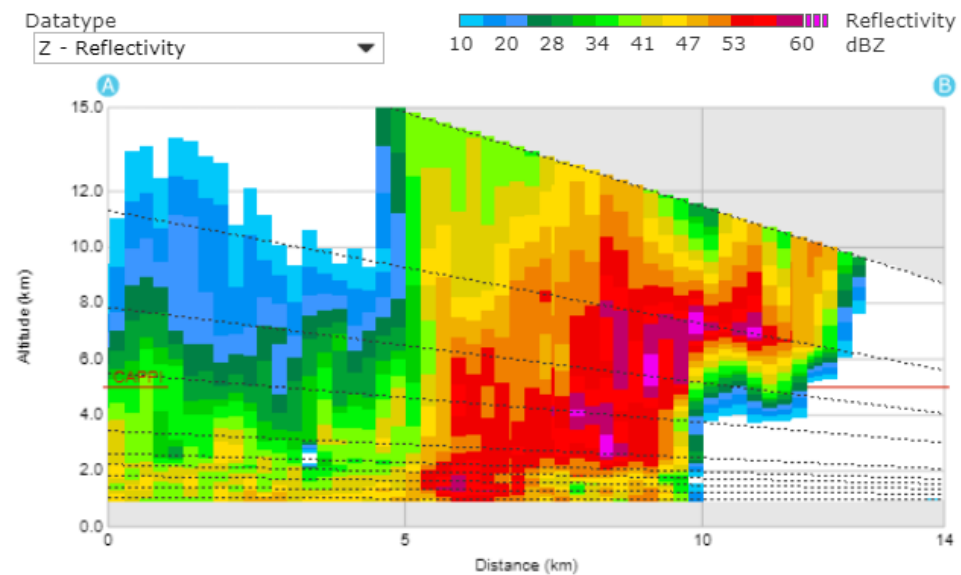
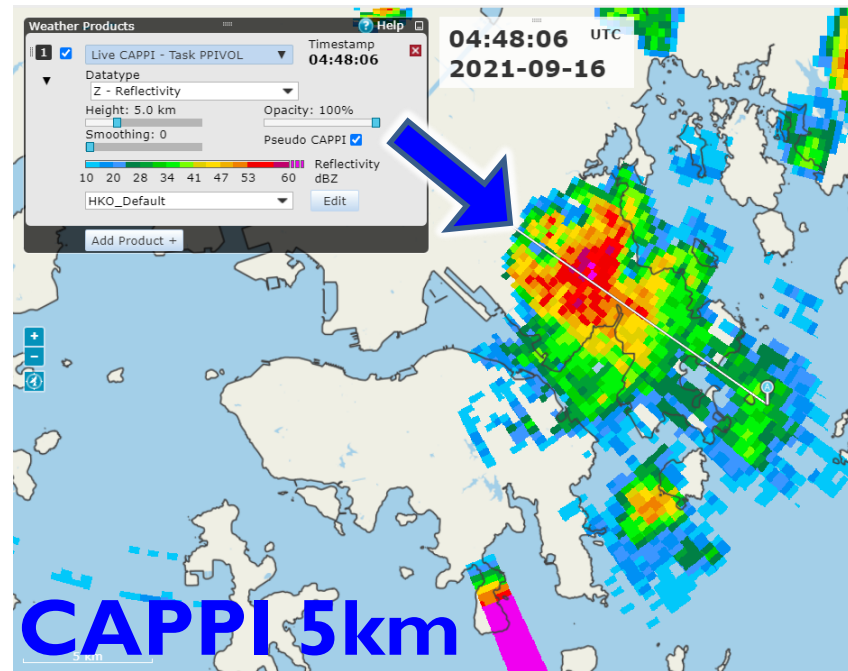
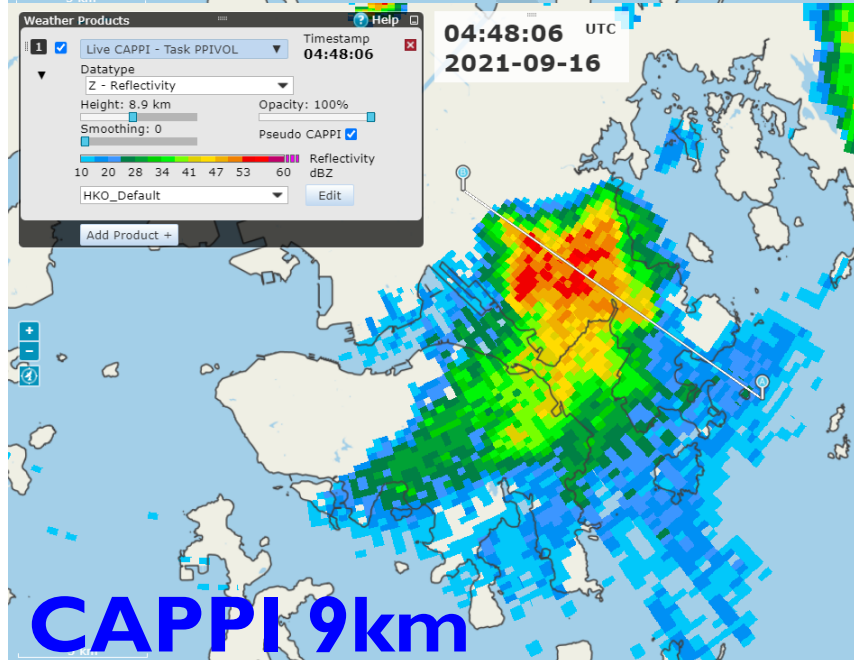
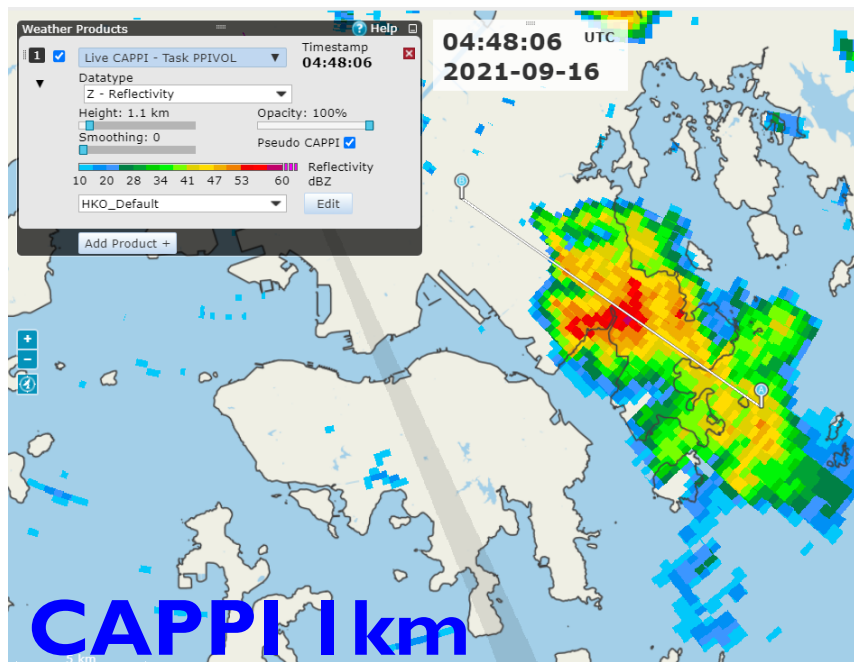
- Hail
 - Large reflectivity (> 60 dBZ) above freezing level with weak echo region (WER) underneath
 - Overhang signature in vertical cross section
- Indicator
 - Echo top (TOPS) of 58-dBZ > 3 km
 - Vertical Integrated Liquid (VIL) in 0-2 km layer < 5 mm



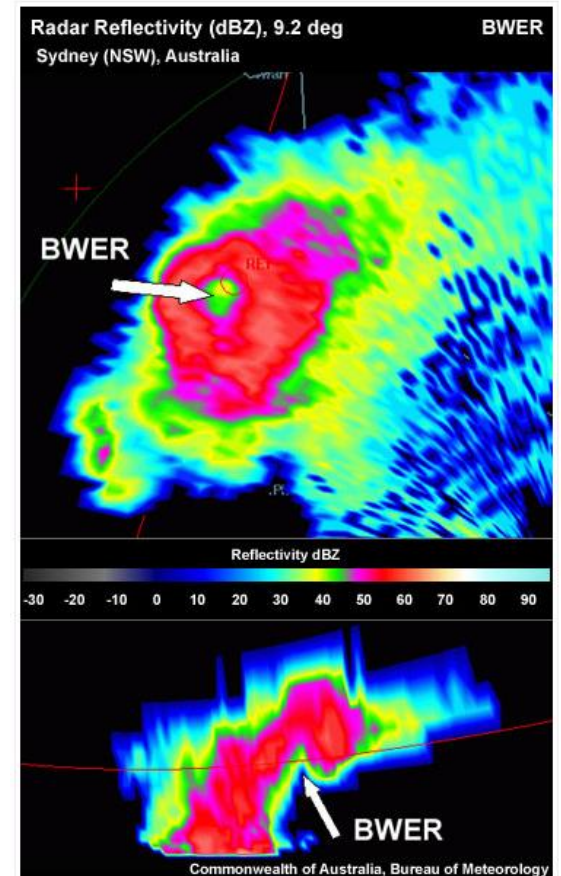
Severe Thunderstorms



- Updraft is strong, with sign of **rotation** (mesocyclone).
- In the strongest updraft, the air becomes supercooled even at temperatures as low as -40°C . On weather radar, this region of supercooled updraft air appears as **weak echo region**. This is a characteristics for hail formation.
- Accompanied with weak echo region, there is often **overhang**, which is another characteristics for hail formation.



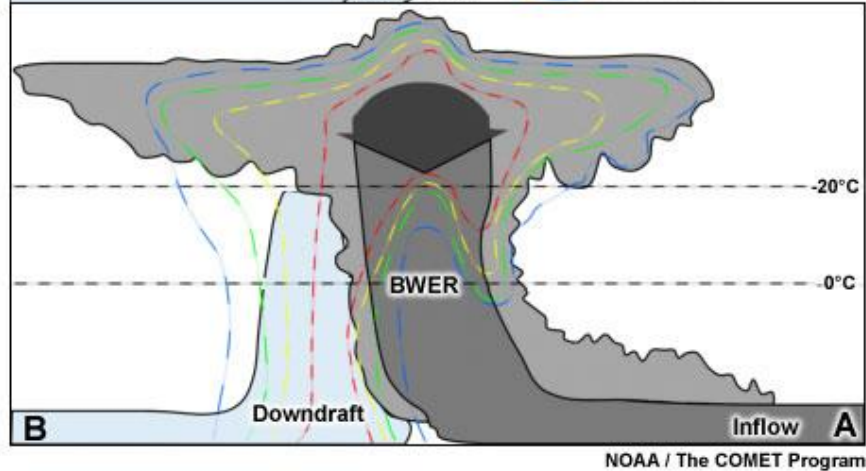
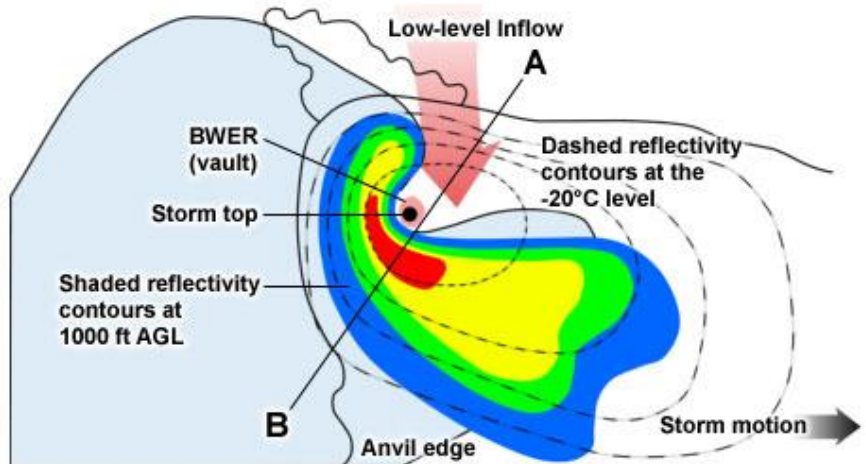
Bounded Weak Echo Region



A "classic" BWER located in the centre of the ring shape in the PPI; a "grim reaper" shape representing the BWER in the RHI.

reference

Conceptual Diagram of a Bounded Weak Echo Region



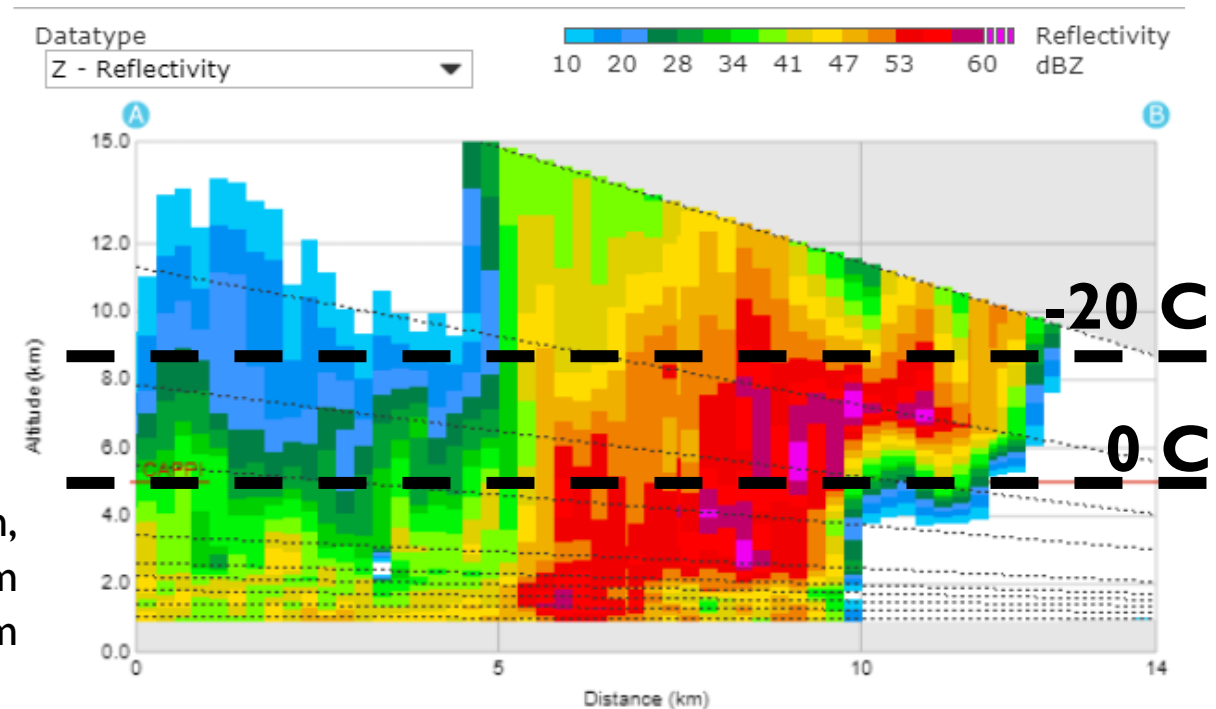
NOAA / The COMET Program

“The presence of a BWER indicates the thunderstorm possesses **an intense updraft** ... BWERs are almost always associated with **supercells** ...

Persistent BWERs, as reasonably reliable proxies for supercells, suggest that the storm is capable of producing **damaging winds, large hail** and, on occasion, tornadoes. ...”

([meted: radar for severe convective weather](#))

Reddish top up to 10km
Intense core (> 60dBz) around 5-6 km



Based on 00Z tephigram,
Freezing level : ~4900m
-20C: ~8500m

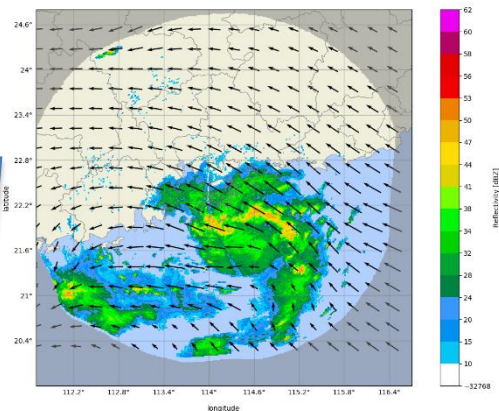
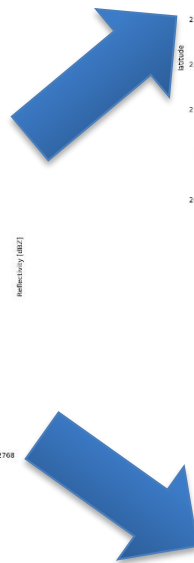
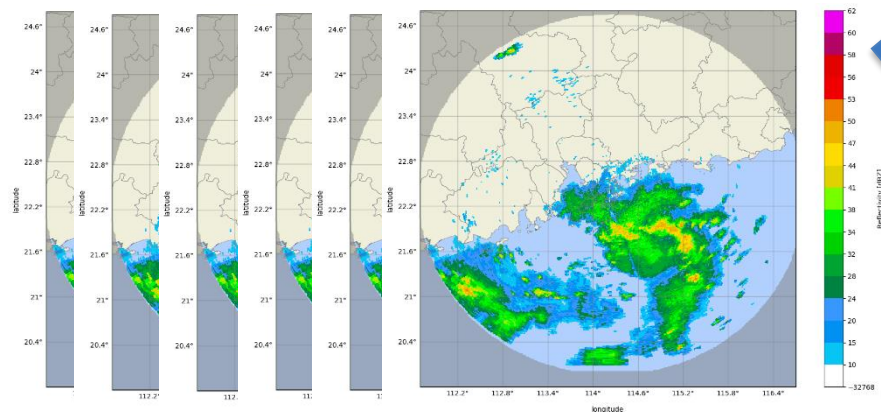
Deep Learning Nowcast

AI in Precipitation Nowcasting

Motion of radar echoes from
computer vision tracking

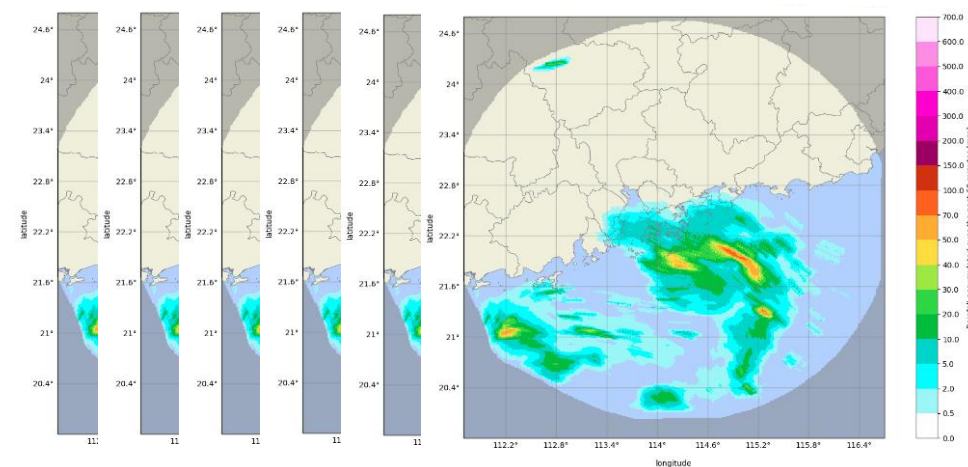
Sequence of actual radar images

$\{X_{t-m}, X_{t-m+1}, \dots, X_{t-1}, X_t\}$



Rainfall or significant convection nowcasts

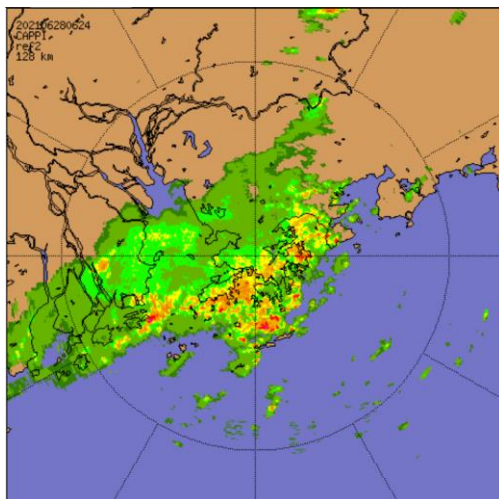
$\{R_{t+1}, R_{t+2}, \dots, R_{t+n-1}, R_{t+n}\}$



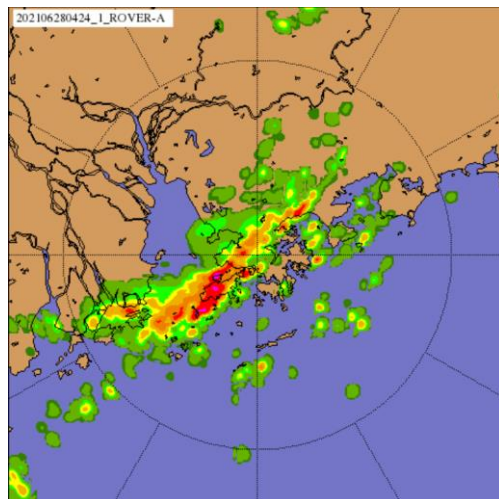
Deep Learning Model

Two-hour radar reflectivity nowcasts from optical flow and DL models

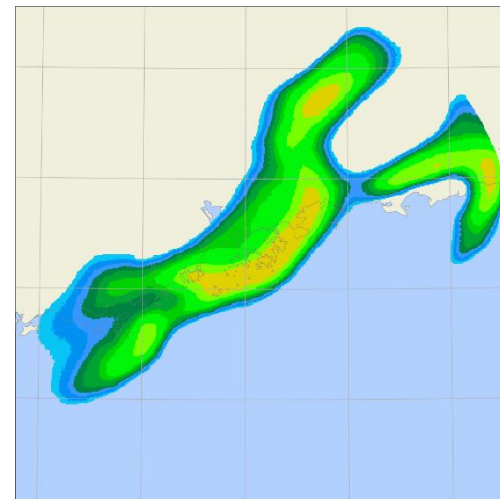
Actual



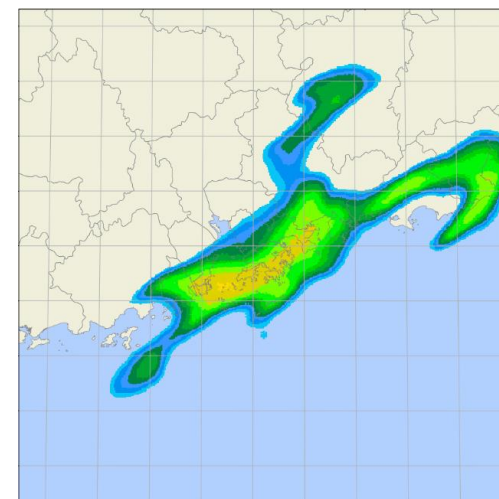
Optical flow



ConvLSTM



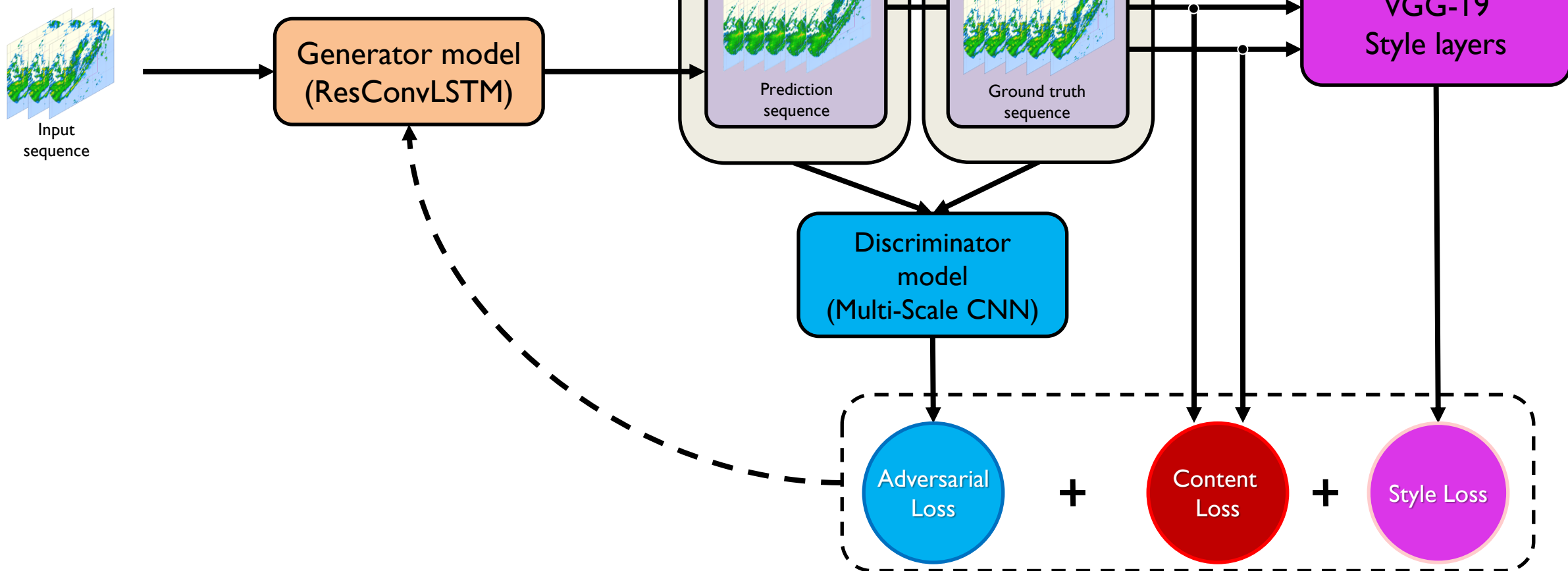
TrajGRU



- Better at predicting the movement and intensity evolution radar reflectivity than extrapolation using gridded optical flow field
- Generally, sequence-to-sequence video prediction model trained with simple loss function (MSE / MAE) faces the blurring problem.

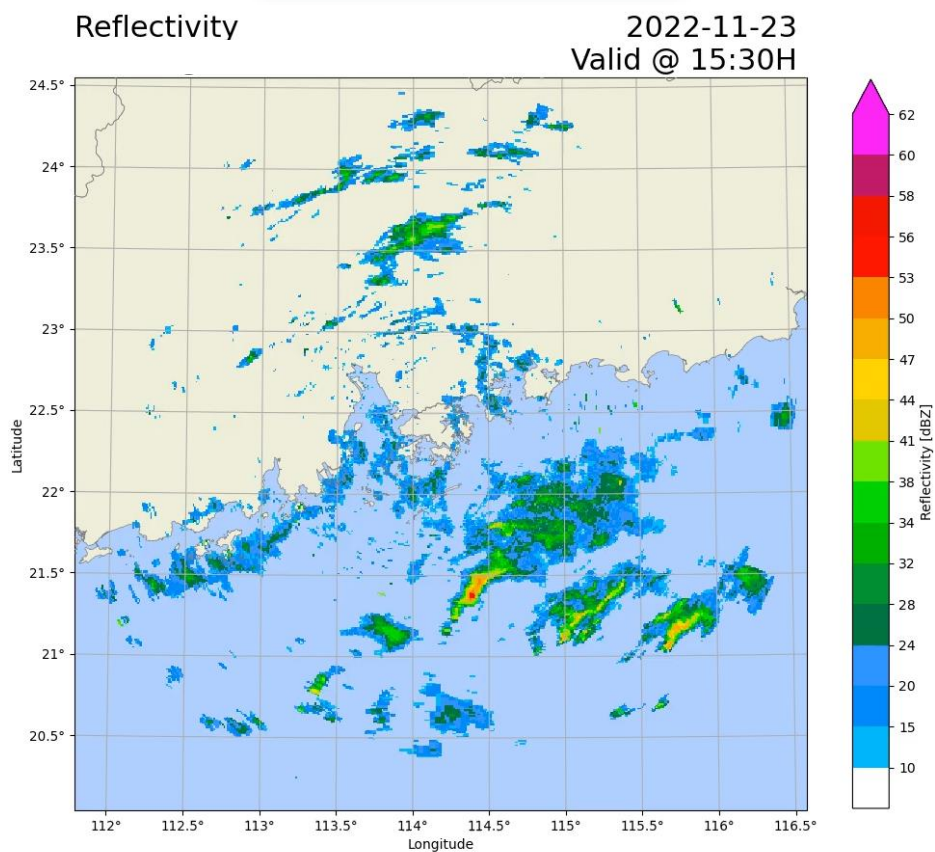
ResConvLSTM-GAN

- **ConvLSTM** with **residual** connections in encoder-forecaster network
- **Generative Adversarial Network (GAN)** to improve representation of small-scale features

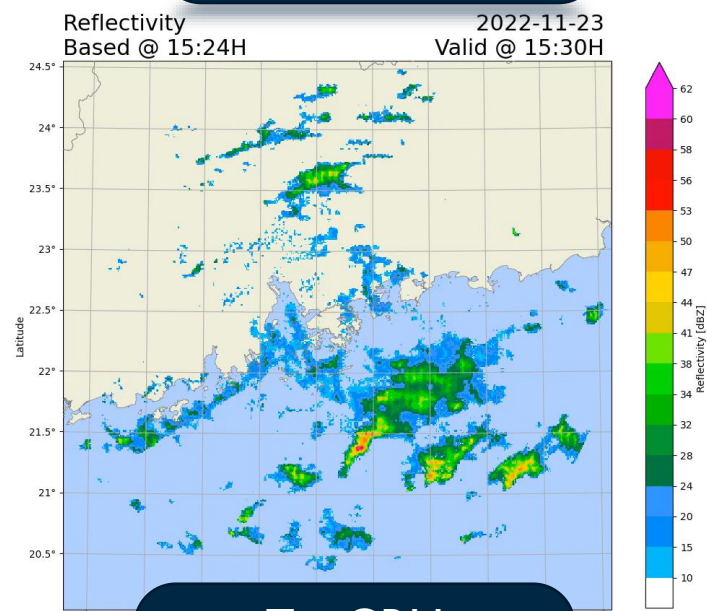


Application of ResConvLSTM-GAN

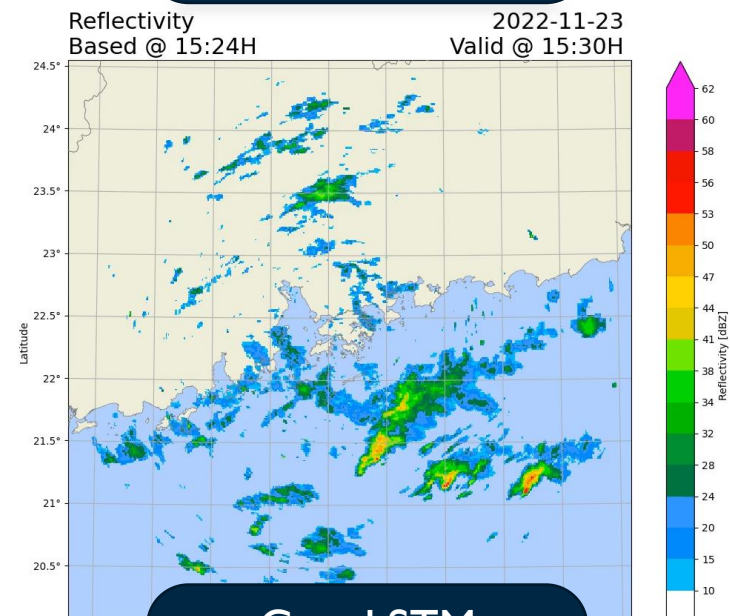
Actual Observations



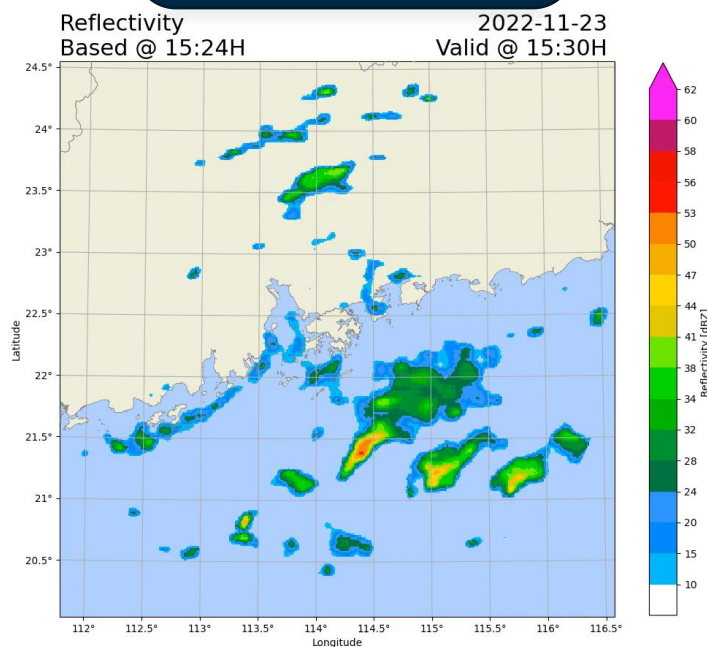
ResConvLSTM-GAN



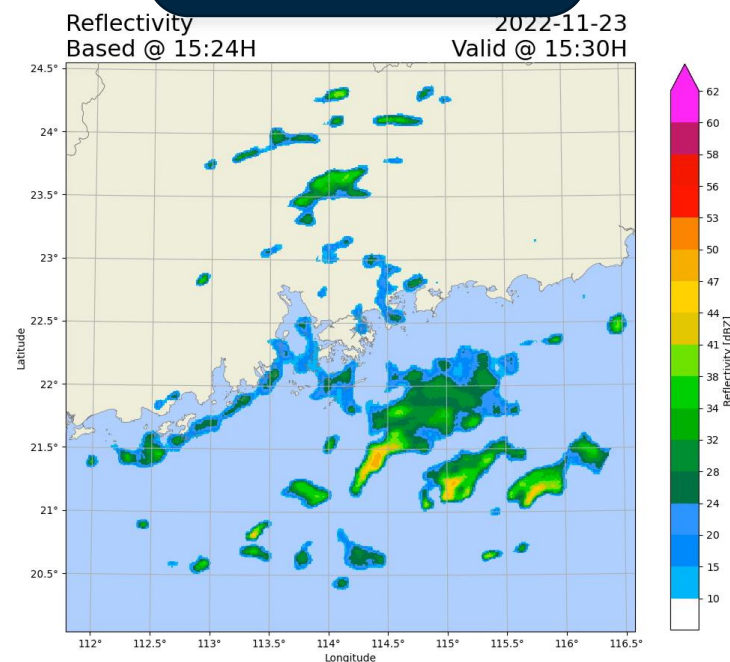
Optical Flow



TrajGRU



ConvLSTM



Evaluation metrics (I)

- Accuracy measures

- Probability of Detection (POD)
- False Alarm Ratio (FAR)

$$POD = \frac{H}{H + M}$$

$$FAR = \frac{F}{H + F}$$

- Skill measures

- Critical Success Index (CSI)
 - Note CSI is not equitable score as CSI is non-zero for constant “yes” forecast or random forecast
- Heidke Skill Score (HSS)
 - An equitable score as HSS is zero for constant or random forecast

$$CSI = \frac{H}{H + M + F}$$

$$HSS = \frac{POC - POC_{\text{random}}}{1 - POC_{\text{random}}} = \frac{(H + Z) - (H_{\text{random}} + Z_{\text{random}})}{N - (H_{\text{random}} + Z_{\text{random}})}$$

$$H_{\text{random}} = \frac{(H + M)(H + F)}{N} \quad Z_{\text{random}} = \frac{(Z + M)(Z + F)}{N}$$

		Observed	
		Yes	No
Forecast	Yes	Hit (H / TP)	False Alarm (F / FP)
	No	Miss (M / FN)	True Negative (Z / TN)

$N = \text{no. of samples} = H + F + M + Z$

Percentage of correct (POC):

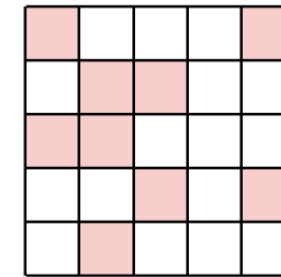
$$POC = \frac{H}{H + Z}$$

Evaluation Metrics (2)

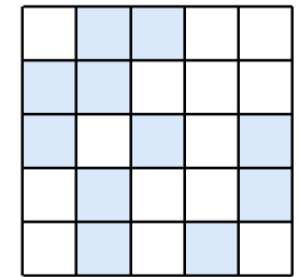
- Fraction Skill Scores (FSS)
 - Fuzzy verification to better represent forecast skills due to double penalty

$$FSS = 1 - \frac{\sum_N (P_{fcst} - P_{obs})^2}{\sum_N P_{fcst}^2 + \sum_N P_{obs}^2}$$

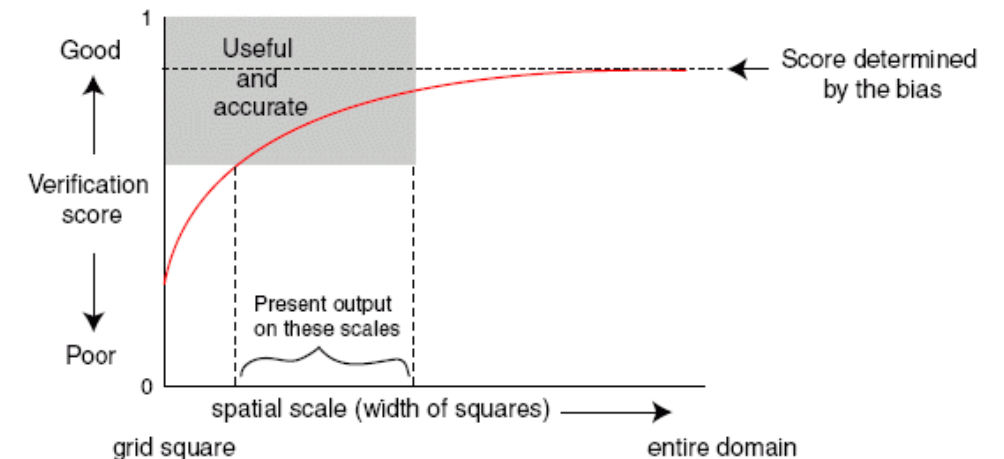
$$P = \frac{\sum \mathbb{1}\{x \geq threshold\}}{h \cdot w}$$



$$P_{fcst} = \frac{9}{25}$$



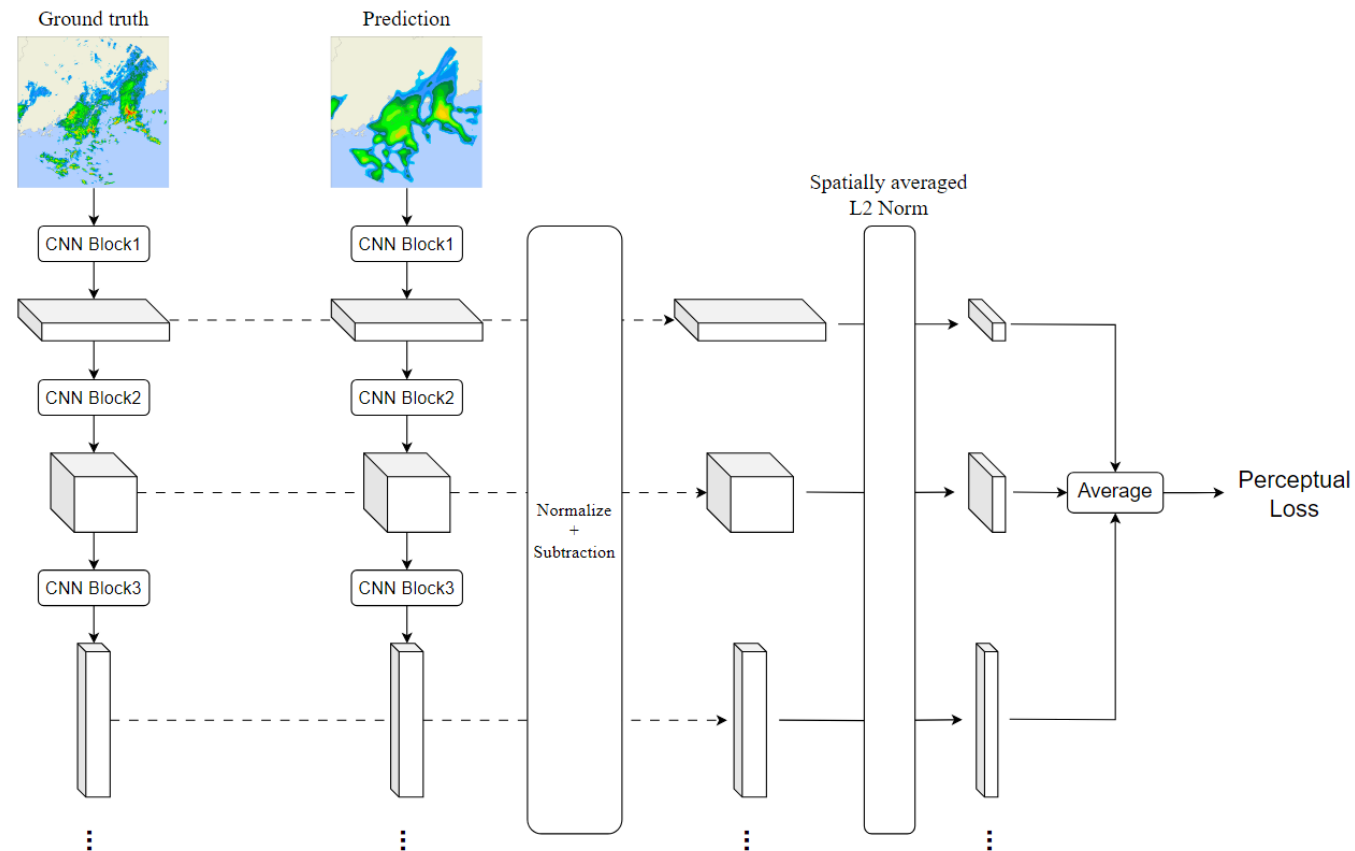
$$P_{obs} = \frac{11}{25}$$



Evaluation Metrics (3)

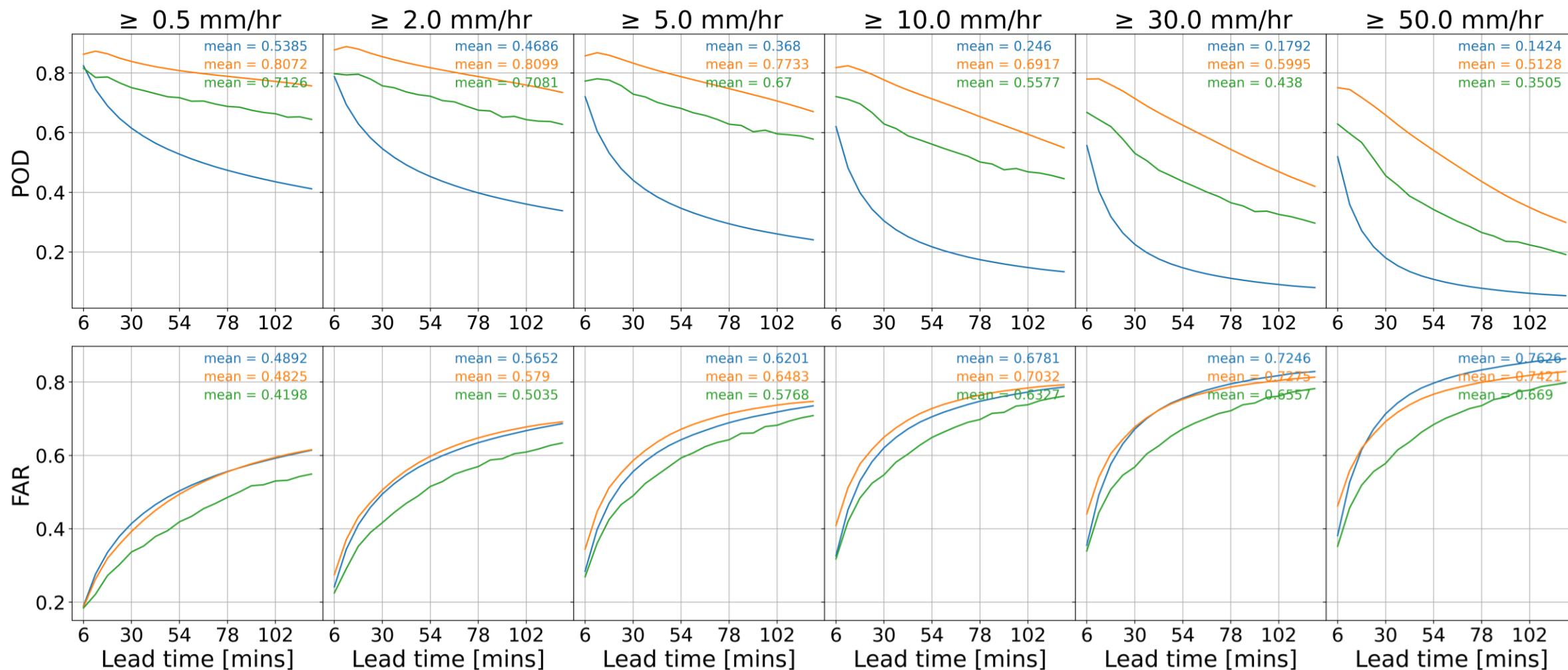
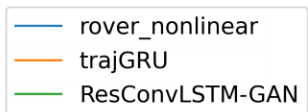
- Learned Perceptual Patch Similarity (LPIPS)

- also known as “Perceptual Loss”
- a neural network (NN) based metric to match human perception → a lower LPIPS score indicates a higher similarity
- measure the difference of activations in a pre-defined NN between 2 images
- a common pre-defined NN: AlexNet



Verification

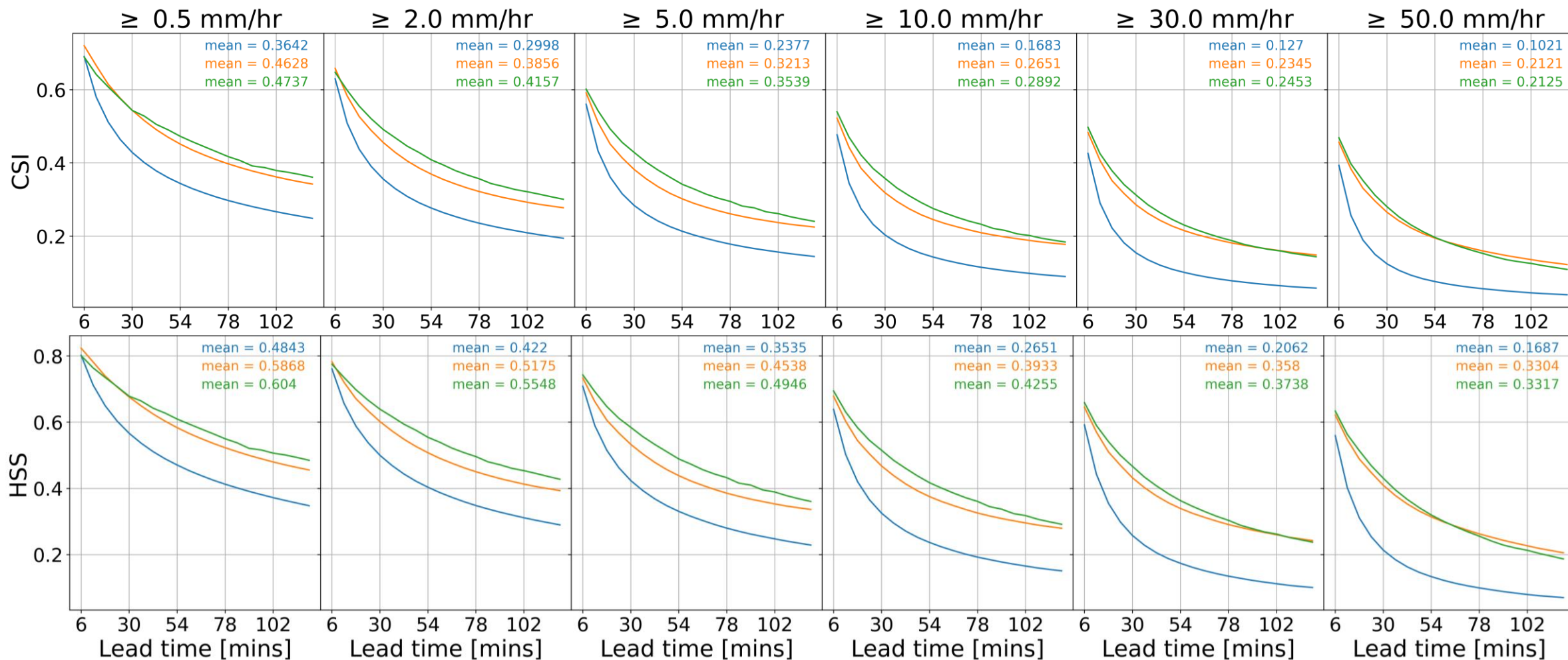
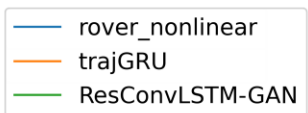
- AI Methods > ROVER;
- RCLG produces less blurry output, so it has lower POD and FAR

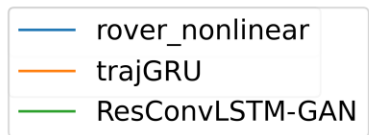


Note: POD – Probability Of Detection ; FAR – False Alarm Rate

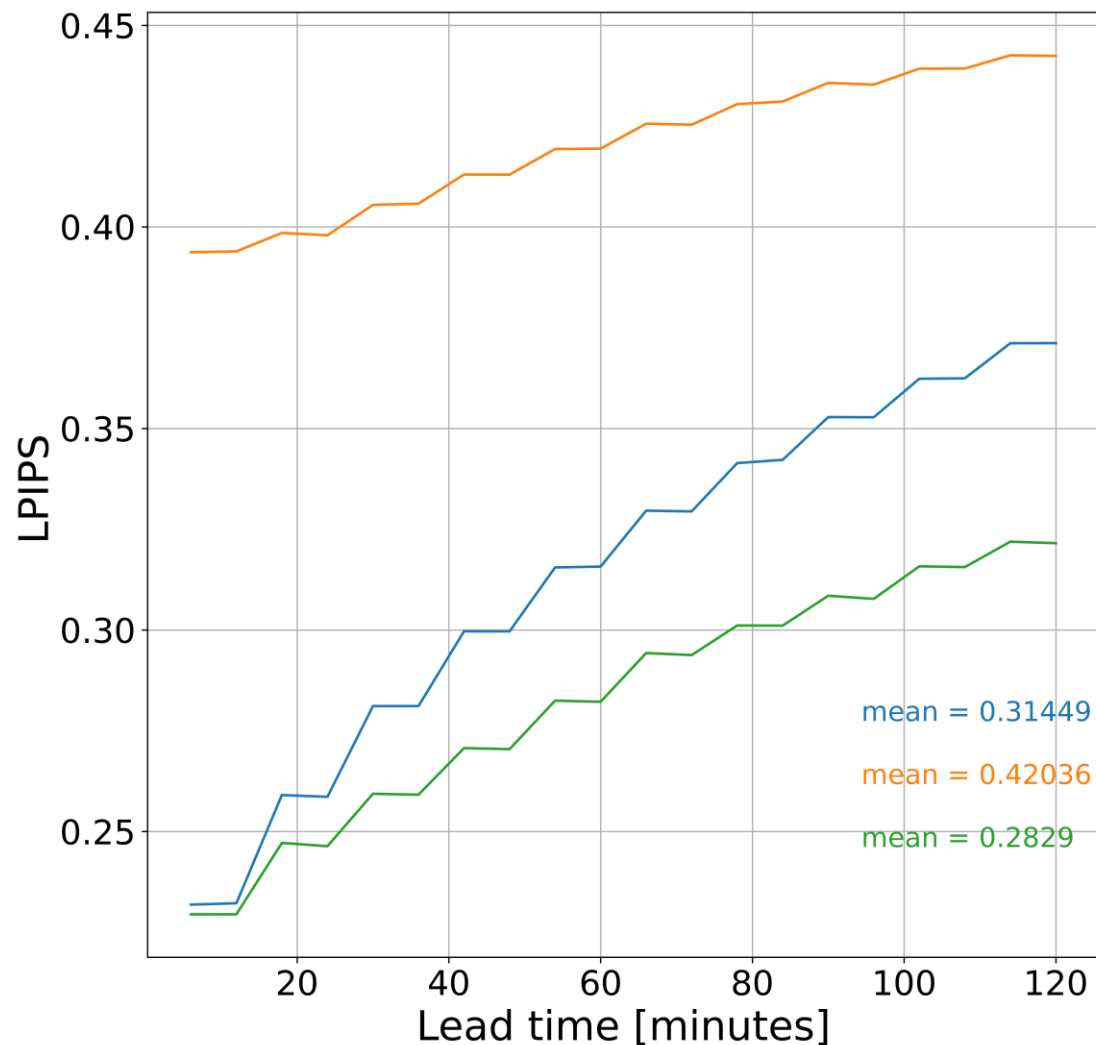
Verification

- RCLG has better overall skills compared to TrajGRU





LPIPS - Lead time plot



Verification

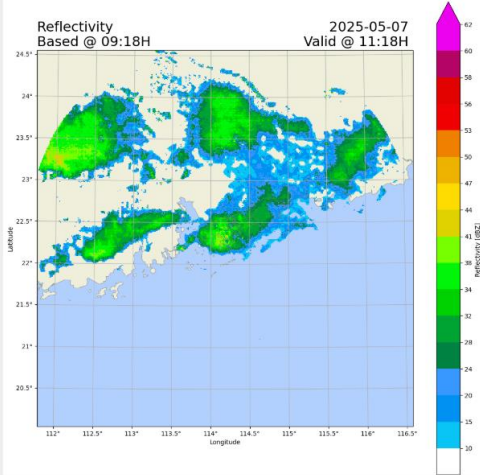
- Learned Perceptual Patch Similarity (LPIPS) metric
 - A Neural Network(NN)-based metric to match human perception, lower the better
 - Measure the difference of activations in a pre-defined NN between 2 images
 - Pre-defined NN: AlexNet
- TrajGRU-generated outputs are perceptually dissimilar while RCLG could generate more realistic outputs

Recent Updates on Deep Learning of Radar Nowcasting

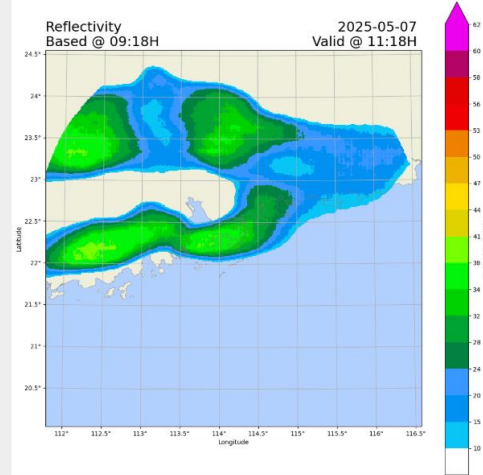
T+120 min nowcasts from deep learning models

2025-05-07 11:18 HKT

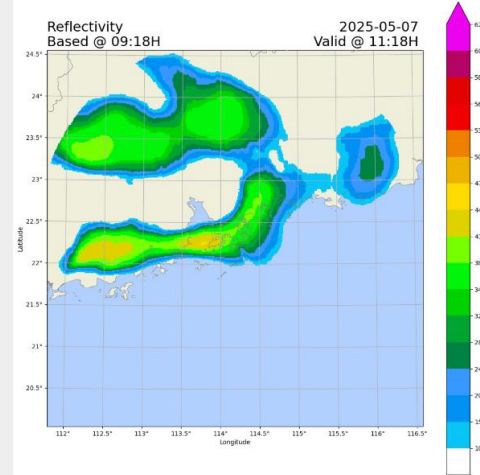
ResConvLSTM-GAN



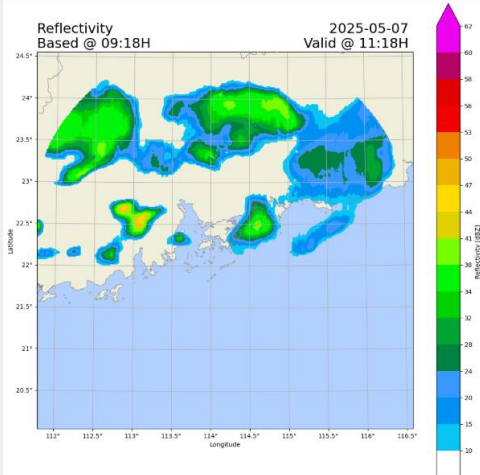
TrajGRU



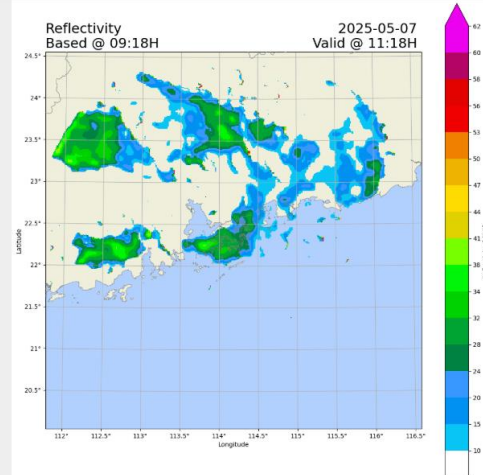
Earthformer



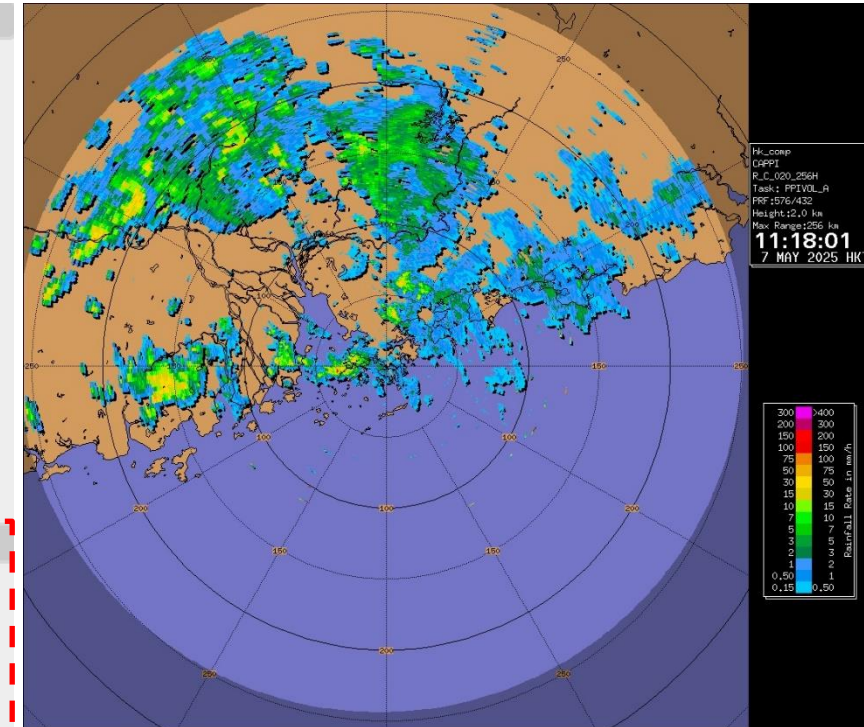
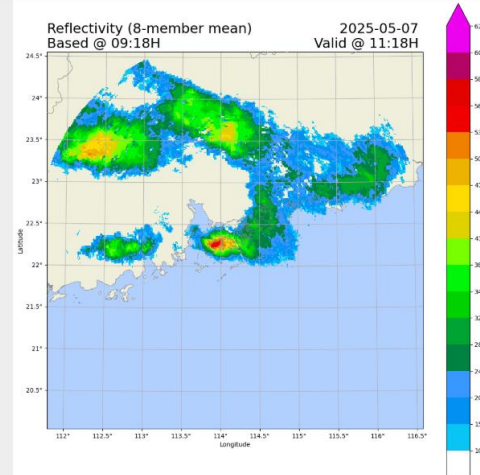
IAM4VP



Fourier



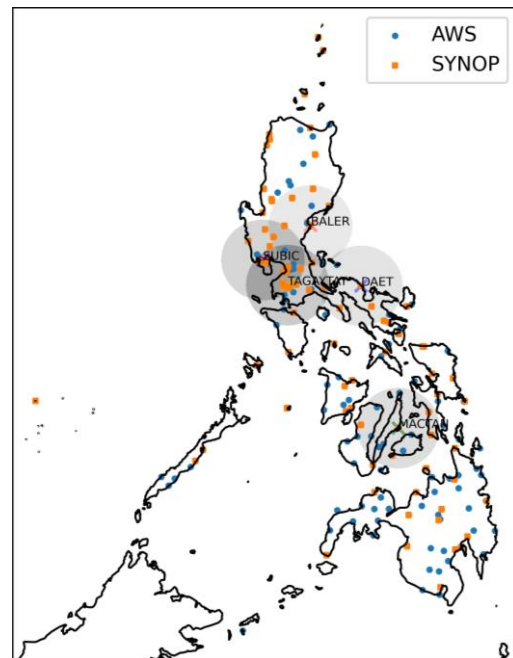
Diffusion Ensemble Mean



AI nowcast models generally pick up stronger echoes over HK (except more eastward location in IAM4VP) in 2-hr forecast

Earthformer and Diffusion Ensemble capture more intense development over HK and coastal region

Collaboration with **PAGASA** and **TMD** in knowledge transfer and implementing Com-SWIRLS and deep learning nowcast models

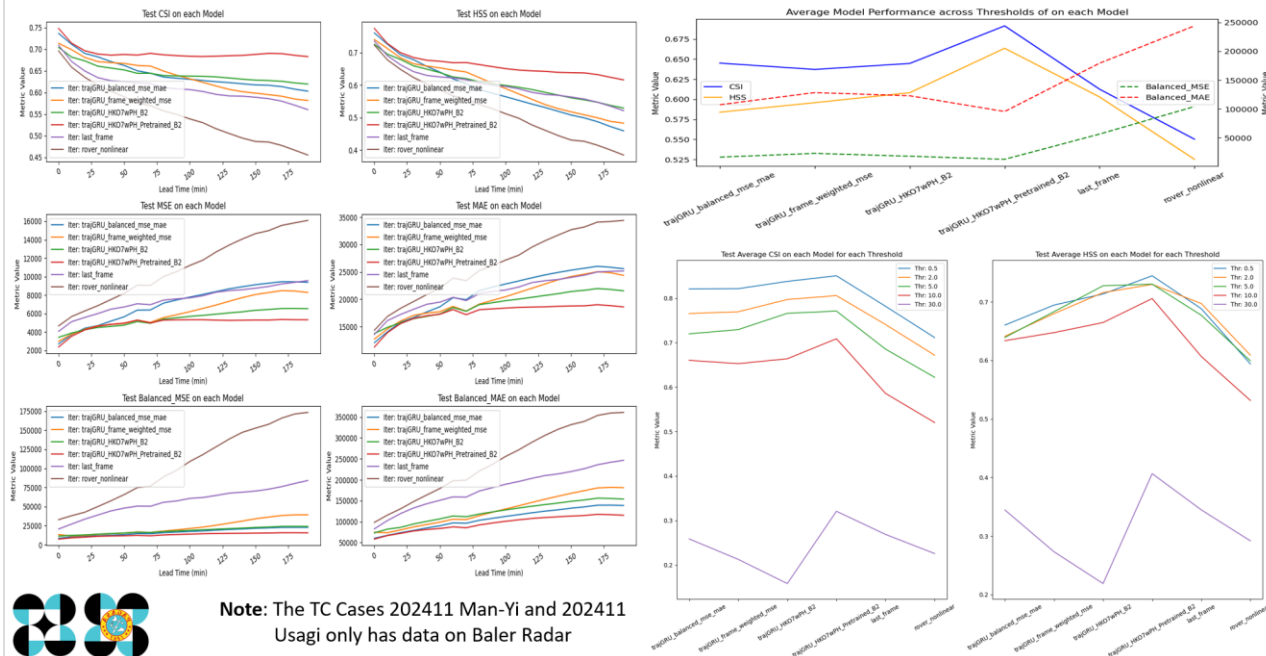


Model Training: TrajGRU with Pretraining, Individual Radars



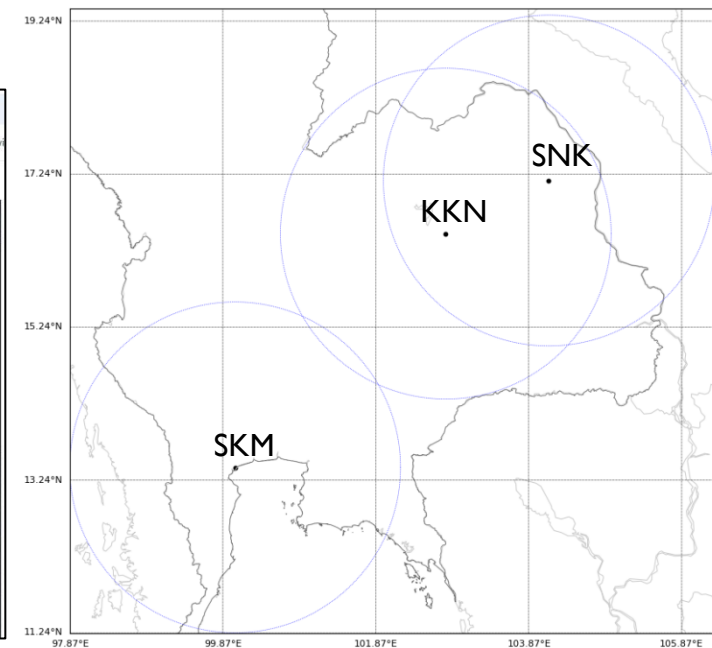
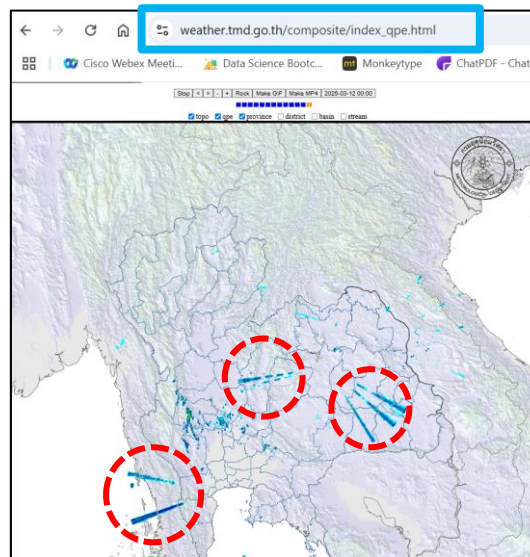
Model Training Lasted 5.254 days at 100,000 iterations

Model Evaluation – Test TC Data



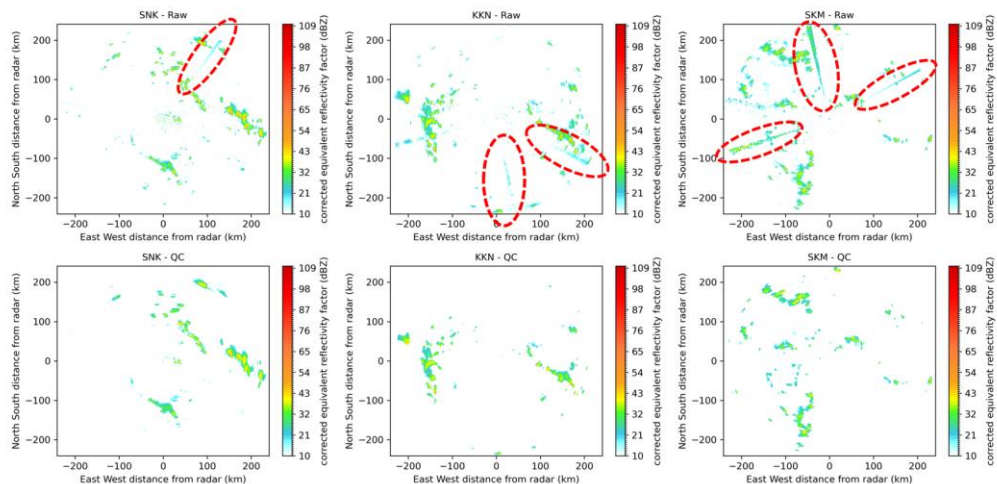
Note: The TC Cases 202411 Man-Yi and 202411 Usagi only has data on Baler Radar

Collaboration with **PAGASA** and **TMD** in knowledge transfer and implementing Com-SWIRLS and deep learning nowcast models



Radar Composite in PPI Lowest Elevation Technique

PPI Reflectivity for SNK, KKN, SKM 2022-09-01T0800Z



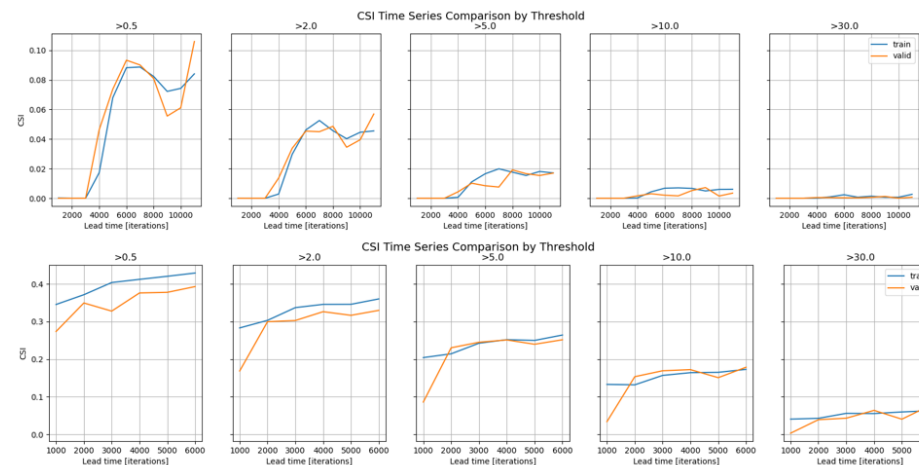
TrajGRU Model

Xingjian Shi, Zhihan Gao, Leonard Lausen, Hao Wang, Di-Yan Yeung, Wai-kin Wong, and Wang-chun Woo, 2017:
 Deep learning for precipitation nowcasting: A benchmark and a new model

Worked for TrajGRU Model: Result (TH only VS TH + HKO7 – KKN site) (After revising mask file and frequency sequence time)

TH only

TH + HKO7





Thank you very much

Q&A

