1. Introduction

The term “nowcast” is a contraction of “now” and “forecast”, and is commonly used to refer to very short-range, advection-based precipitation prediction using radar observations. According to the Glossary of Meteorology of the American Meteorological Society, a nowcast is defined as “a short-term weather forecast, generally for the next few hours” (American Meteorological Society 2017). Nowcasts differ from other types of weather forecasts because there is no strict standard for the lead time. The U.S. National Weather Service specifies zero to three hours as the target period for operational nowcasts (American Meteorological Society 2017). The UK Met Office provides nowcast products up to 6 hours ahead (Met Office 2017), and the new High-resolution Precipitation
tion Nowcasts published by the Japan Meteorological Agency (JMA) in 2014 focus on rainfall within the next 30 minutes (Japan Meteorological Agency 2017).

Naturally, the lead time and accuracy of nowcasts are important aspects for their use in both public and private applications. Flood prevention and water management organizations require forecasts of rainfall amounts that cover the longest period possible during precipitation events. On the other hand, if the objective is to monitor severe local-scale weather events, a lead time of 1 hour or less is of great importance. In Japan, the occurrence of extremely localized and short-lived torrential rainfall has attracted public attention since a number of such events in 2008 resulted in fatalities (see below). However, there is no strict definition for this type of rainfall. The most appropriate classification in the JMA forecasting glossary is “localized heavy rainfall” (LHR), which is defined by four characteristics: rapid strengthening, precipitation up to several dozens of millimeters, occurrence within several tens of minutes, and occurrence over a small area (Japan Meteorological Agency 2015). The total amount of LHR may be relatively small, but its intensity can be extremely high. For example, on 28 July 2008, the water level in the Toga River in Kobe City rose by more than 1 m in 10 minutes following an LHR event, resulting in flash floods and five fatalities (Fujita and Kunita 2010). One week later, another LHR occurred in the Zoshigaya district in Tokyo. This LHR exceeded 100 mm h$^{-1}$ within 20 minutes and then maintained an intensity of more than 100 mm h$^{-1}$ for 35 minutes over an area of less than 5 km$^2$ (Kato and Maki 2009). The LHR led to the death of five workers who drowned in a sewerage tunnel. As this LHR was concentrated in a very small area, it was not successfully captured by the operational C-band radar network (1-km spatial resolution), and the operational precipitation nowcast system was unable to correctly predict its intensity (Kato and Maki 2009). Drowning and flooding following LHR have been reported worldwide in recent years. Large cities are particularly at risk from LHR and typically suffer significant damage when these events occur. The JMA has reported that the annual number of events having extreme hourly rainfall rates has increased over the past 40 years (Japan Meteorological Agency 2013). Furthermore, as a result of the global climate change, the frequency and intensity of short-duration (hourly or sub-hourly) and small-spatial-scale rainfall are projected to increase further in the future (Westra et al. 2014). Therefore, an accurate prediction of LHR is important if we are to build resilient cities. However, numerous studies have found that small-scale, isolated storms are typically more difficult to forecast because their features are less persistent than those of larger, more organized storms (Grecu and Krajewski 2000; Van Horne et al. 2006; Germann et al. 2006). As LHR events may be only a few kilometers in spatial scale and have lifespans of less than 1 hour and as they often occur without being triggered by any organized convective system, their accurate prediction remains a challenging problem.

However, the evolution of radar technology, especially the use of X-band radar, as well as the amount of high-resolution spatial and temporal observations available, is making prediction of LHR increasingly possible. In particular, since the X-band polarimetric (multi-parameter) RAdar Information Network (XRAIN) project was launched in 2010, 38 X-band polarimetric radars have been installed to cover most of the major cities in Japan (Maesaka et al. 2011). Each of the XRAIN radars samples the atmosphere in increments of 150 m in range and of less than 1.2° in the azimuth. The maximum observable range of each radar is up to 80 km, with a quantitative observation range of 60 km. The radars are spaced approximately 40 km apart and arranged so that intensive observation areas are covered by multiple radars, enabling the rain attenuation of individual radars to be corrected using a composite scheme. The specifications of the XRAIN radars have been described by Maesaka et al. (2011). The XRAIN observations provide high-resolution data that capture the growth or dissipation occurring inside a storm, which should enable improvements in the prediction of LHR.

In addition, although efforts have been made to extend the skill limit of nowcasts to longer lead times (e.g., Dixon and Wiener 1993; Johnson et al. 1998; Seed 2003; Ebert et al. 2004), little attention has been paid to the initial stage of precipitation events, despite the fact that an error of 5–10 minutes in the timing of the predicted initiation of an event can cause serious problems, especially in the case of LHR. Within this context, our motivation for this study is to develop a nowcast system that is able to provide precise information when a precipitation event is imminent by using the vertically integrated liquid (VIL) water content estimated from volume scan observations. Several attempts have been made to apply VIL in weather forecasting. For example, Kitzmiller et al. (1995) used VIL as an indicator of severe local storms in the WSR-88D Severe Weather Potential algorithm, and Amburn and Wolf (1997) suggested that a high VIL density can provide the ability to access hail potential.
Furthermore, Boudevillain et al. (2006) developed the RadVil model to improve advection rainfall forecasting schemes. Ishihara (2013b) applied the RadVil model to thunderstorms in Tokyo on August 5, 2008, with 10-minute resolution radar data, but found it was difficult to identify the rainfall peak accurately. Nevertheless, the capability of VIL remains debatable because of 1) unstable model performance relating to fluctuations in the relationship between VIL and the radar reflectivity factor \( Z \) and 2) less contribution to maintaining the skill in the case of longer lead times. The scope of this study is limited to imminent rainfall prediction, for which we modify the RadVil model and develop an algorithm to estimate VIL from polarimetric radar parameters. The nowcast system we propose is called VIL Nowcast. The remainder of this paper is organized as follows. Section 2 describes the radar mode and measurements, and introduces the three precipitation events analyzed in this study. Section 3 describes the algorithm used for VIL estimation and the formulation and implementation of VIL Nowcast. Section 4 presents and compares results obtained from the three precipitation events. Finally, a discussion and our conclusions are provided in Section 5.

2. Radar data and precipitation events

2.1 Two- and three-dimensional radar data

Two XRAIN radars in the Kanto region of Japan, at Saitama and Shinyokohama, were used in this study to estimate VIL and thereby generate nowcasts. The Saitama radar site (139.633°E, 35.893°N, 172 m above sea level (ASL)) is about 25 km north of central Tokyo, whereas the Shinyokohama radar site (139.599°E; 35.513°N, 62 m ASL) is about 25 km to the south (see Fig. 1 for details). Both radars were operated at 12 elevation angles, which can be classified into two types based on their purposes. The first type is called the delivery-use elevation angle, which is used for both the three-dimensional Constant Altitude Plan Position Indicator (CAPPI) and the two-dimensional rainfall map generation. The second type is used for CAPPI generation only and is called the CAPPI-use elevation angle. The Saitama radar observes delivery-use elevation angles of 1.4° and 2.4°, and CAPPI-use elevation angles of 0.8°, 3.6°, 4.9°, 6.3°, 7.9°, 9.7°, 11.8°, 14.2°, 16.9°, and 20°. The Shinyokohama radar observes delivery-use elevation angles of 1.7° and 2.6°, and CAPPI-use elevation angles of 1°, 3.8°, 5.1°, 6.5°, 8.1°, 9.9°, 11.9°, 14.2°, 16.9°, and 20°. The

Fig. 1. Observation area and simulation domain of VIL Nowcast. Red triangles mark the position of the radars used in this study, and blue triangles indicate the other radars which were not used in this study in the XRAIN Kanto region. Solid circles outline the maximum observable area (80 km) of each radar, and dash-dotted circles outline the quantitative observation area (60 km) of each radar. The black rectangle in the right panel marks the nowcast domain.
The specific differential phase shift ($K_{\text{DP}}$) at each radar site is estimated via $R$ (e.g., Park et al. 2005a, b; Maki et al. 2010; Maesaka et al. 2011; Tsuchiya et al. 2015). The data were provided by the National Institute for Land and Infrastructure Management (NILIM).

Table 1. Technical specifications of the Saitama and Shin-yokohama radars.

|                        | Saitama     | Shinyokohama |
|------------------------|-------------|--------------|
| Frequency              | 9.75 GHz    | 9.77 GHz     |
| Peak radiated power    | 100 kW      |              |
| Beam width             | 1.04° (H) / 1.06° (V) / 1.05° (H, V) |
| Pulse width            | 1 µs        |              |
| PRF                    | Dual, 1800 Hz / 1440 Hz |
| Range increment        | 150 m       |              |
| Azimuth increment      | 1.2°        |              |
| Antenna rotation speed  | 3.5 rpm for delivery elevation angles; 4.5 rpm for CAPPI elevation angles; |
| Data products          | $Z$, $K_{\text{DP}}$, $Z_{\text{DR}}$, $R$, and Quality flags |

Three-dimensional CAPPI data were generated from the XRAIN volume scan using the NIED procedure. All volume scan measurements collected by the two radars with overlapping coverage were integrated and interpolated onto CAPPI grids with a grid spacing of 19.8° in longitude and 16.2° in latitude (a spatial resolution of approximately 500 m) via a modified Cressman interpolation scheme that used an ellipsoidal influence zone. The vertical resolution of the CAPPI data is 250 m, and the grids extend to a height of 12 km.

The Tokyo metropolitan area is situated in the Kanto Plain to the northwest of Tokyo Bay and is flanked by mountains to the west. Consequently, it experiences strong coastal and orographic influences. To take into account the thunderstorms triggered by the sea breeze from the southeast and the orographic precipitation over the hilly terrain to the west, an area within the Shin-yokohama radar’s maximum observable area was chosen as the nowcast domain (black rectangle in Fig. 1). This nowcast domain spans a longitudinal range of 139.00° to 140.21°E, and a latitudinal range of 35.00° to 35.99°N.

2.2 Precipitation events

Considering the objective of VIL Nowcast is to improve the performance of imminent rainfall prediction, especially for LHRs, we selected an extremely small-scale rainfall, a typical LHR, and a wide-range rainfall event caused by a front in August 2011 as case studies for analysis. The atmospheric conditions during these events are shown in Fig. 2.

On 6 August (CASE1, Figs. 2a, b, c-1), the atmospheric state at 0900 Japan Standard Time (JST, GMT + 9) could not typically be described as unstable. The 0°C isotherm was located at 560 hPa, about 5 km ASL. The relative humidity (RH) below this altitude was above 70 %, with the maximum (98 %) at 900 hPa in the vicinity of an inversion. The amount of precipitable water from the surface to 300 hPa was 60.0 kg m$^{-2}$. The lifting condensation level (LCL) was 972 m above ground level (all subsequent heights are expressed relative to the ground level), and little convective available potential energy (CAPE) was available for parcels ascending above 900 hPa. According to the XRAIN radar observations, one small-scale echo appeared at 1530 JST at Toda-shi, Saitama, (around 139.6°E, 35.9°N; see Fig. 3a), and it had increased in intensity to more than 70 mm h$^{-1}$ within 5 minutes of its appearance. This echo faded out after 1615 JST, but excited several more intensive echoes to the north.

Technical specifications of these two radars are listed in Table 1. To obtain a higher-temporal-resolution rainfall map at lower elevations, XRAIN operates in a multi-use scan mode, which performs three PPI scans every minute with two delivery-use elevation angles repeating every 2 minutes in alternate shifts with the CAPPI-use elevation angles repeating every 5 minutes. Therefore, each radar implements a volume scan with 15 elevation angles in each 5-minute period, and at the same time, generates a rainfall intensity map for lower elevations every minute.

The XRAIN two-dimensional product includes $Z$, the specific differential phase shift ($K_{\text{DP}}$), the differential reflectivity ($Z_{\text{DR}}$), the rainfall rate ($R$), and the quality flag. Its quality control, attenuation correction, and algorithm for parameter estimation are based on the procedure developed at the National Research Institute for Earth Science and Disaster Resilience (NIED) (e.g., Park et al. 2005a, b; Maki et al. 2010; Maesaka et al. 2011). The $R$ at each radar site is estimated via the $K_{\text{DP}}$-$R$ relationship, when $K_{\text{DP}}$ is available below the melting layer; otherwise, the $Z$-$R$ relationships are applied with different coefficients for below, above, and within the melting layer (Maesaka et al. 2011). Then, the rainfall intensities from all radars belonging to the same intensive observation area are interpolated onto a horizontal grid with a grid spacing of 11.25° in longitude and 7.5° in latitude (a spatial resolution of approximately 250 m). All polar coordinate grid points under 5,000 m were taken into consideration using the weighted Cressman interpolation method when generating the XRAIN composite rainfall map (Tsuchiya et al. 2015). The data were provided by the National Institute for Land and Infrastructure Management (NILIM).
with peaks at around 1640 JST. The whole precipitation event finished at approximately 1800 JST.

The atmospheric conditions at 0900 JST on 7 August (CASE2, Figs. 2a, b, c-2) were rather unstable compared with CASE1. A ridge extended to the eastern Japan region in the morning (Fig. 2a-2). Driven by high pressure, the temperature in the Kanto region increased rapidly. By 1200 JST, the surface temperature and relative humidity at 900 hPa in Tokyo were above 35°C and 90 %, respectively, while over the ocean to the south, the temperature was about 30°C and the relative humidity was above 80 %. The 0°C isotherm

Fig. 2. (a) Surface weather maps at 0900 JST on 6 (a-1), 7 (a-2), and 26 (a-3) August, 2011. (b) JMA-mesoscale analysis (JMA-MANAL) at 1200 JST on the same dates as (a). Wind barbs indicate the wind at 10 m above the surface (m s⁻¹), and contours and shading show the surface temperature and the relative humidity at 900 hPa, respectively. (c) Observed sounding from Tateno (star in (b)) plotted on a standard skew T–log p diagram, for 0900 JST on each day.
was situated at about 5 km ASL, the precipitable water amount was 56.3 kg m\(^{-2}\). The LCL was at 977 m, the level of free convection (LFC) was 1433 m, and CAPE was 1,419 J kg\(^{-1}\) at 0900 JST. Several isolated storms were generated within the target area from the early afternoon onwards (see Fig. 3b). The Tokyo station (location shown in Fig. 5) of the Automated Meteorological Data Acquisition System (AMeDAS) recorded rainfall between 1540 and 1610 JST with a peak of 11 mm for a 10-minute period beginning at 1550 JST.

The precipitation event on 26 August (CASE3, Figs. 2a, b, c-3) was caused by a stationary front. The surface weather map for 0900 JST in Fig. 2a-3 shows a stationary front lying 180-km north of the target area, and a low-level convergence can be identified at 1200 JST from the surface wind pattern in Fig. 2b-3. Large parts of Tokyo and surrounding areas experienced heavy rainfall during the afternoon (data not shown). The maximum 10-minute rainfall amount recorded at the AMeDAS Nerima station (see Fig. 5) was 27.0 mm at 1520 JST, and the 1-hour rainfall amount from 1500 to 1600 JST was 89.5 mm. According to Tokyo flood data published by the Bureau of Construction, Tokyo Metropolitan Government (2017), more than 400 buildings experienced flooding during this precipitation event, and all of these flooding events were caused by urban surface runoff. The water level of the Shakujii River briefly reached a level that required local evacuation, and the operation of the Marunouchi Line (Tokyo Metro) was suspended temporarily because of the rising level of the Kanda River.

3. Methodology

The VIL Nowcast system consists of the VIL estimation phase and the rainfall nowcasting phase. The accurate retrieval of the water content and VIL from the radar parameters is essential for the creation of an accurate nowcast because this provides the input for the nowcasting phase. The rainfall nowcasting phase includes the estimation of the advection vector, the formulation and initialization of VIL Nowcast, and time evolution. As the focus of this research is to predict the initial stage and sudden onset of extreme LHR ahead of time, a fast and effective heuristic is required. Therefore, this model was designed to 1) quickly capture the development of rainfall from the radar observations; 2) precisely predict rainfall 10 minutes ahead of time; and 3) be easy to run on a stand-alone PC to allow distribution to users such as local government organizations and private companies.

3.1 VIL estimation

The VIL Nowcast system makes use of the VIL estimated from the polarimetric radars. The classic estimation method for water content \((M)\) is based on the \(Z-M\) relationship (Greene and Clark 1972). However, it is well known that the actual \(Z-M\) relationship
varies in both time and space. Boudevillain and Andrieu (2003) proposed the use of distinct coefficients in the \(Z-M\) relationship on the lower and upper parts of the 0°C isotherm and the interpolation of reflectivity factors within the melting layer, although the improvement afforded by this method was not conclusively proven. On the other hand, the development of the polarimetric radar raises the possibility of obtaining more accurate water content measurements. In this context, a number of studies have shown that using polarimetric radar measurements can improve rain measurements (Zrnić and Ryzhkov 1996; Bringi et al. 2003; Ryzhkov et al. 2005); therefore, in this study we have improved on the method developed by Hirano and Maki (2010) by estimating VIL from a combination of \(Z\) and \(K_{DP}\). The method proposed by Hirano and Maki (2010) uses the \(K_{DP}-M\) relationship to estimate the water content of intense rainfall, and applies the \(Z-M\) relationship to less intense rainfall. However, as the drop size distribution (DSD) varies with time, a homogeneous \(Z-M\) relationship is undoubtedly inadequate for the precise estimation of the water content. As Maki et al. (2005b) suggested that \(K_{DP}\) was less sensitive to variations in DSD than was \(Z\), we developed a process for the readjustment of the \(Z-M\) power law equation. In general, the water content \(M (\text{kg m}^{-3})\) can be estimated as follows:

\[
\begin{align*}
M(K_{DP}) &= a_1 \times K_{DP}^{b_1}, \\
M(Z) &= a_2 \times Z^{b_2},
\end{align*}
\]

where \(a_1, b_1, a_2, \) and \(b_2\) are coefficients determined by regression analysis. Maki et al. (2005b) proposed the values of 0.991 and 0.713 for \(a_1\) and \(b_1\), respectively, based on a comparison of the radar and disdrometer data obtained at Tsukuba, Japan, from a total of 19,749 drop spectra. These values have been proved effective in estimating \(M\) during precipitation events in Tokyo (e.g., Hirano and Maki 2010; Kim et al. 2012). Hence, we regarded the \(K_{DP}-M\) relationship as constant in this research, although its coefficients are also perturbable over space and time in a strict sense. Assuming that the values of \(a_1 = 0.991\) and \(b_1 = 0.713\) for \(K_{DP}-M\) are appropriate for estimating the water content at \(K_{DP} \geq 0.3^\circ\text{km}^{-1}\) (Park et al. 2005b), a correction function can be obtained by replacing \(M\) in Eq. (2) with Eq. (1) and taking the logarithm of both sides, as follows:

\[
\log(0.991 \times K_{DP}^{0.713}) = b_2 \times \log(Z) + \log(a_1).
\]

After determining \(a_2\) and \(b_2\) by regression analysis, the corrected \(Z-M\) relationship was used to estimate the water content at grid points where \(K_{DP} < 0.3^\circ\text{km}^{-1}\) or where \(Z < 35\text{ dBZ}\), which are the same thresholds as those used by Park et al. (2005b) for radar-rainfall estimators. Consequently, the VIL (\(\text{kg m}^{-3}\)) estimator can be expressed as follows:

\[
\begin{align*}
\text{VIL} = \begin{cases} 
0.991 \times \int_0^h K_{DP}^{0.713} \, dh, & \text{if } K_{DP} < 0.3^\circ\text{km}^{-1} \text{ or } 10\log_{10} Z < 35\text{ dBZ} \\
(3) 
\end{cases}
\]

where \(h\) (m) is the height of the top of the echo observed by the radar. Note that the units of \(Z\) in Eq. (4) are \(\text{mm}^6\ \text{m}^{-3}\). The relationship between the water content and radar reflectivity is retrieved by assuming that all raindrops are in the liquid phase; the accuracy of this relationship varies with the precipitation circumstances. This assumption may lead to errors when a large number of solid precipitation particles are present.

3.2 Nowcasting algorithm

a. Advection vector estimation

The advection vector in the VIL Nowcast model is retrieved from the rainfall field using the spatial correlation method, which represents the average motion vector for the whole domain without identifying individual rainfall cells. Considering the target rainfall type of VIL Nowcast, this assumption may lead to substantial errors in some circumstances because small-scale features often display more erratic motions and shorter lifespans, which also make them less predictable (Germann and Zawadzki 2004). However, we decided to use the spatial correlation method for two reasons. First, in convective cases, the prediction accuracy of the correlation method is similar to that of cell-tracking methods (Pierce et al. 2004). Second, it is helpful to evaluate the effect of including the precipitation aloft individually by comparison with the existing rainfall-rate nowcast model developed by Kato et al. (2009b), in which the same advection scheme was applied. In addition, the correlation method is simple and quick and is essential for the successful operational nowcasting of imminent precipitation events. Herein, the average motion vector was calculated at each time step from two successive VIL images, \(VIL(t)\) and \(VIL(t-1)\), taken 5 minutes apart, after applying a low-pass filter as a pre-processing step and using the fast Fourier transform (FFT) autocorrelation approach (see Kato et al. 2009b). This average motion vector \((u, v)\) was used to advect the VIL field and
retain its uniformity throughout the whole nowcast period.

b. Formulation and Initialization

The forecasting scheme follows the RadVil model proposed by Boudevillain et al. (2006), which expresses the rainfall process in a conceptual way using precipitation source terms. The RadVil model assumed that fluctuations in VIL in an atmospheric column between two successive volume scans were caused by precipitation (the output term) and the apparent sources, which included the net effects of vapor condensation, coalescence, and melting, etc. Therefore, the source term \( S(t) \) (kg \( m^{-2} \) s\(^{-1}\)) at a given time \( t \) (s) can be obtained by subtracting the ground rainfall rate \( P(t) \) (kg \( m^{-2} \) s\(^{-1}\)) from the change in VIL (kg \( m^{-2} \)):

\[
\frac{dVIL}{dt} = S(t) - P(t),
\]

where

\[
\frac{d}{dt} = \frac{\partial}{\partial t} + u \frac{\partial}{\partial x} + v \frac{\partial}{\partial y},
\]

is the two-dimensional advection operator, and \( u \) and \( v \) (m s\(^{-1}\)) are the horizontal components of the advection vector in the \( x \) and \( y \) directions, respectively. The falling velocity of raindrop is not considered. Both \( P(t) \) and VIL can be estimated from the radar observations by assuming that the radar-measured rainfall rate is equivalent to the rainfall rate on the ground. Another important assumption in the RadVil model (Boudevillain et al. 2006) is that at a given time, the VIL in an atmospheric column is equal to the ground rainfall rate multiplied by the response time, \( \tau \) (s). In other words, it will take a time \( \tau \) for all rain drops in the atmospheric column to reach the ground if the rainfall rate is \( P(t) \). However, this assumption cannot be satisfied if no rainfall rate was observed on the ground \( (P(t) = 0) \). Intense echoes may be detected aloft even though there is no precipitation on the ground; however, the RadVil model is unable to recreate this situation. This difference between the precipitation observed aloft and on the ground is one of the major advantages of using VIL Nowcast to predict rainfall ahead of time. Herein, in contrast to the RadVil model, we add an intercept term to the linear approximation when establishing the relationship between VIL and the radar-derived rainfall rate to take advantage of the time difference between the raindrops observed aloft and on the ground as follows:

\[
VIL(t) = \tau(t) \cdot P(t) + w(t),
\]

where \( w \) (kg \( m^{-2} \)) represents the raindrops observed aloft even though no rainfall has been observed on the ground yet.

The parameters \( S(t) \), \( \tau(t) \), and \( w(t) \) are the variables used to solve the time evolution equation. \( S(t) \) can be retrieved from the VILs of the pairs of successive volume scans at the time \( t \) and \( t - \Delta t \), and the two-dimensional rainfall rate \( P(t) \) from the following equation:

\[
S(t) = \frac{VIL(t) - VIL(t - \Delta t)}{\Delta t} + P(t).
\]

The star symbol in Eq. (8) indicates that the field of \( VIL(t - \Delta t) \) has been advected by the advection vector \((u, v)\) referred to above to exclude the influence of rainfall field movement as suggested by Boudevillain et al. (2006). \( \Delta t \) equals the volume scan period, which was set to 5 minutes in this study. Assuming that the response time and the additional term have the same value in the whole domain, \( \tau(t) \) and \( w(t) \) were calculated from \( VIL(t) \) and \( P(t) \) at time \( t \) using the least squares method. Note that \( \tau(t) \) is set to 1 s in the case when the return is smaller than a predetermined threshold (0.01 s in this study). This setting avoids the generation of anomalous values but might induce discontinuity in the results. Then, a pair of \( \tau(t) \) and \( w(t) \) is applied to the whole domain and remains constant during the nowcasting period, although strictly speaking, the relationship between VIL and the rainfall rate is not homogeneous over time and space.

c. Forecasting temporal evolution

Using Eq. (7) to replace the rainfall rate \( P(t) \) in Eq. (5), we obtain:

\[
\frac{dVIL}{dt} + \frac{VIL(t)}{\tau(t)} = S(t) - \frac{w(t)}{\tau(t)}. 
\]

This is a first-order inhomogeneous linear differential equation. If we denote variables at the current time as \( S(t_0) \), \( \tau(t_0) \), and \( w(t_0) \) and regard them as constant over the time step during the nowcasting, VIL at the next time step \( VIL(t + dt) \) can then be obtained as follows:

\[
VIL(t + dt) = VIL(t) \cdot e^{-\frac{dt}{\tau(t_0)}} \left[ 1 + \tau(t_0) \left( S(t_0) - \frac{w(t_0)}{\tau(t_0)} \right) \left( 1 - e^{\frac{-dt}{\tau(t_0)}} \right) \right].
\]
where $VIL^*/(t)$ is the advected field of $VIL(t)$ using the advection vector $(u, v)$ mentioned previously. The time step $dt$ is taken to be short enough to ensure the continuity of the rainfall; we used a time step of 20 seconds in this study. Note that in the case that the advection velocity could not be obtained from the autocorrelation approach, an observational area-averaged wind vector at the 600-hPa isobaric level from the JMA mesoscale model (MSM) forecast was used instead to advect the field of $VIL(t)$. However, this may introduce errors caused by disagreements between the upper-level wind and the movement of the rainfall field.

To obtain the rainfall amount, the VIL at each time step was converted into the rainfall rate $P$ using Eq. (7) again, and the accumulated rainfall was calculated every 10 minutes, as shown in Fig. 4. Although the focus of VIL Nowcast is on the very short range, in particular for 10 minutes ahead, the model was designed to produce forecasts up to 1 hour ahead to enable comparisons with existing models. Therefore, the output of the VIL Nowcast model consisted of six rainfall amounts covering 10-minute periods from the current time to 1 hour ahead. The product was updated automatically every 5 minutes. The VIL Nowcast model takes less than 30 seconds to produce the 1 hour forecast on a personal computer running an Intel Xeon 3.5 GHz processor with 32 GB of RAM.

4. Results

In this section, the performance of the VIL Nowcast model is compared with XRAIN observations and a rainfall-rate nowcast model developed by Kato et al. (2009), which was also designed for very-short-term nowcasting of torrential rainfall by using the same advection vector scheme and predicting 10-minute rainfall up to 60 minutes ahead. The XRAIN rainfall rate was used as the input for the rainfall-rate nowcast model. Although the accuracy of XRAIN has been assessed by numerous previous studies, such as Tsuchiya et al. (2015) and Kim and Maki (2012), strictly speaking, the rainfall observed by XRAIN was not equal to the rain gauge observations because the targets were observed at different heights in each case. Our results focus on the difference between radar observations and predictions, whereas ground truth verification is not considered because CASE1 and CASE2 were too small to be accurately detected by AMeDAS. Nevertheless, a comprehensive verification of VIL Nowcast should involve a comparison with ground observations, considering many precipitation events at various scales. We plan to undertake this verification in the near future. Hereafter, VIL Nowcast will be abbreviated as VIL_NC, and the reference rainfall-rate nowcast model as RR_NC. The XRAIN rainfall rate was used as input for the RR_NC. Section 4.1 shows the result of the first prediction of the analysis period, Section 4.2 compares the lead time and threshold dependence during the whole prediction period, and Section 4.3 compares the possible lead time from two different models for sounding alarms.

4.1 First prediction

The VIL_NC predictions for the approximate peak in intensity of each precipitation event are shown in Fig. 5, together with the XRAIN rainfall amount for the first prediction period (10 minutes ahead). XRAIN observations at a particular time are calculated as the accumulation of XRAIN rainfall rate (converted to
Fig. 5.  XRAIN observations (left column) vs VIL Nowcast predictions (right column). (a, a'): CASE1; (b, b'): CASE2; (c, c'): CASE3. In prediction panels, shading indicates the predicted 10-minute-accumulated rainfall amount for 10 minutes ahead, and solid black (dashed grey) contours show predictions for 30 (60) minutes ahead at 10 mm and 30 mm levels. The black star in each panel marks the representative point used for the time series in Fig. 7. Triangles denote nearby AMeDAS stations.
mm per minute) from 9 minutes earlier to the current time. The rainfall field from the prediction agrees with the XRAIN observations, and the maximum 10-minute rainfall exceeds 10 mm (equivalent to an intensity of 60 mm h$^{-1}$) in all events, but VIL_NC slightly overestimates the rainfall amount. The assumption in the VIL_NC algorithm could contribute to the overestimation, since it represents precipitation as the bulk liquid water in the column without considering its vertical distribution and the falling velocity of rain drops, and it allows an intercept in the VIL–rainfall-rate relationship.

The correlation between the first VIL_NC prediction and the XRAIN observations is shown in the upper panels of Fig. 6 as density scatterplots for the three precipitation events. All grid cells with non-zero rainfall amount in either XRAIN observations or VIL_NC (RR_NC) predictions are included in the scatterplots. Among the three studied cases, the VIL_NC’s coefficient of determination ($R^2$) for CASE1 showed the lowest value at 0.79 and increased with the spatial–temporal scale of rainfall to a value of 0.87 for the synoptic-scale case (CASE3). The lower panels in Fig. 6 show a similar comparison between XRAIN and RR_NC. The RR_NC predictions also show the highest $R^2$ for the synoptic storm (CASE3, 0.89) and the lowest $R^2$ (0.76) for CASE1. Previous studies have reported that nowcasting performs well in situations such as frontal systems that move over several hours, covering large distances while largely preserving their structure (e.g. Germann and Zawadzki 2002; Turner et al. 2004). The satisfactory performance of both models in the synoptic case is consistent with these findings; in particular, the predictions generated by RR_NC show a greater improvement, relative to VIL_NC, for CASE3 when compared with CASE1 and CASE2. On the other hand, the VIL_NC predictions are slightly better than those of RR_NC for the two isolated storms (CASE1 and CASE2), which are usually difficult to predict using existing nowcast systems. The VIL_NC biases for CASE1–3 were 0.10, 0.22, and 0.37, respectively, and those for RR_NC were 0.33, 0.46, and 0.22, respectively. In addition, the areas of large sample numbers in the RR_NC
results (red color in Fig. 6), extending along the x-axis especially for CASE1 and CASE2, indicate that RR_NC is unable to predict the precipitation at numerous grid cells. This may have been caused largely because of the initial part of the precipitation event (as explained later). Overall, the regression line in Fig. 6 indicates that VIL_NC follows a trend of overestimation compared with XRAIN, whereas RR_NC tends to underestimate. The larger sample size (N) of VIL_NC also indicates a tendency to overestimate. More than 93 % of the differences in N were caused by samples with a value of less than 1 mm for 10-min rainfall.

The time series of 10-minute rainfall amounts at representative points (the position of the point in each case is shown as a black star in Fig. 5) are shown in Fig. 7. The representative point was randomly chosen from among the areas of most intense rainfall in each case. In CASE1 (Fig. 7a), the observed rainfall starts to increase at 1540 JST, exceeding 5 mm at the next time step and reaching its first peak of 10 mm 10 minutes later, at 1550 JST. The increase in the first 10 minutes is equivalent to the rate of 60 mm h$^{-1}$, but the strong rainfall (> 5 mm, equivalent to the rate of 30 mm h$^{-1}$) lasts for only 15 minutes and decreases to below 4 mm at 1620 JST. Both VIL_NC and RR_NC overestimate the first peak, with predicted values of around 14 mm. However, VIL_NC predicts the first non-zero value of 8 mm at 1545 JST and the peak at 1550 JST, which is in agreement with the XRAIN observations, whereas RR_NC shows the first non-zero value of 3 mm at 1550 JST and the peak at 1555 JST. Another small rise of 2 mm occurs at 1720 JST, but dissipates immediately. VIL_NC performs very well in capturing the timing of the precipitation event, including the sharp initial increase at this particular point, whereas the RR_NC predictions are delayed by 5 minutes for both the increasing and decreasing phases of both rainfall peaks. This pattern is also seen in CASE2 (Fig. 7b). The maximum rainfall rate in this case is higher than in CASE1, and although the rainfall at the representative point is relatively weak, there is intense rainfall (> 5 mm, equivalent to a rate of 30 mm h$^{-1}$) between 1455 and 1515 JST. Although VIL_NC briefly drops to 4.5 mm at 1500 JST, it otherwise predicts the intense rainfall period in close agreement with the observations. The time series at the representative point for 26 August (CASE3, Fig. 7c) shows two intense rainfall peaks. Rainfall first increased from 1435 JST and reached a maximum at 1500 JST with a period of intense rainfall between 1450 and 1510 JST. After stopping, the second increase begun at 1520 JST with an intense rainfall period lasting from 1525 JST until 1620 JST. The maximum value is around 15 mm, and the total rainfall amount between 1525 and 1620 JST reaches 70 mm. VIL_NC accurately predicts the timing of these changes, but RR_NC predicts both peaks 10 minutes later than observed. Even though
RR_NC performs slightly better than VIL_NC in statistics such as $R^2$ over the whole precipitation period (Fig. 6f), the delay in the initial stage is nonetheless noticeable.

The RMSE for the whole prediction period at the three representative points is listed in Table 2. These statistics show higher scores for VIL_NC than for RR_NC. Notably, VIL_NC has successfully eliminated the gap between observation and prediction in the initial stage of the precipitation events.

### 4.2 Forecast lead time and rainfall threshold dependence

This section compares the predicted rainfall fields up to 60 minutes ahead against the XRAIN observations at the given times, to assess the performances of VIL_NC and RR_NC over the entire nowcast period. The equitable threat score (ETS; Schaefer 1990) describes the skill of the system in predicting the occurrence of precipitation above selected threshold rates (Germann and Zawadzki 2002). We used the thresholds of 1, 3, 5, 8, and 10 mm for the 10-minute-accumulated rainfall, which were equivalent to hourly accumulations of 6, 18, 30, 48, and 60 mm, respectively. Table 3 lists the number of grids that reached these thresholds for each event based on the XRAIN observations. The motion vector uses an extrapolation-based approach and is considered uniform for the whole forecast domain, which may result in errors for individual isolated cells with less persistent, small-scale precipitation features. Considering the cell scale and motion vector algorithm employed in this study, the ETS skill scores may be expected to decrease rapidly with increasing lead time and thresholds. Figure 8 summarizes the decrease in ETS over the lead times from 10 to 60 minutes for each event. For both VIL_NC and RR_NC, the ETS skills decreased with increasing lead time. For example, at the threshold of 1 mm, the ETS for VIL_NC was around 0.66–0.74 at a lead time of 10 minutes, but it decreased to 0.20–0.36 at a lead time of 30 minutes, and there was little skill beyond that point. Similar behavior was seen for RR_NC for which ETS dropped from 0.61–0.72 at a lead time of 10 minutes to 0.17–0.38 at a lead time of 30 minutes. The rate of decline decreased as the scale of precipitation increased from CASE1 to CASE3, which is consistent with previous findings that large-scale precipitation features are more persistent than smaller features (Grecu and Krajewski 2000; Van Horne et al. 2006; Germann et al. 2006). VIL_NC shows higher skills for the two isolated events (CASE1 and CASE2), but RR_NC performs better for the synoptic-scale event (CASE3), especially at a threshold of 1 mm. The failure of VIL_NC at the 1-mm threshold of CASE3 can be attributed largely to its overestimation of the weak rainfall area. The total “False” area in VIL_NC at the 1-mm threshold, which represents that the nowcast-predicted precipitation exceeded the threshold whereas the observed precipitation did not; this area was 70 % larger than that in RR_NC.

In Fig. 8, it is also apparent that the forecast skill decreases with increasing threshold, although the skill of VILNC$_{TH=3}$ at the lead time of 10 minutes in CASE3 was 0.01 higher than that of VILNC$_{TH=1}$ (Fig. 8c). The ETS of VIL_NC at the lead time of 10 minutes dropped by 0.29, 0.22, and 0.15 over the range of thresholds used here, for CASE1, CASE2, and CASE3, respectively; the equivalent drops for RR_NC were 0.26, 0.22, and 0.17, respectively. For the 6 August event (CASE1), the ETS of the first predictions at 10 minutes by both VIL_NC and RR_NC was less than 0.5 for the thresholds of 8 and 10 mm, suggesting that excessively high thresholds, greater than or equal to 8 mm, should be avoided to obtain accurate forecasts. It is important to note that for most prediction times (except for the 1 mm threshold in CASE3), there was an improvement in ETS for VIL_NC. The greatest improvement was 0.07 for a threshold of 5 mm at a lead time of 20 minutes for the 7 August event (CASE2), while the greatest improvement for the first prediction was 0.05 for a threshold of 3 mm during the 6 August event (CASE1). These enhancements of forecast skills suggest that isolated storms benefit most from the use of VIL_NC.
4.3 Evaluation of the timing of warning alarms

Traditional objective verification methods, such as the ETS and the bias score, are not the most informative from the viewpoint of imminent prediction, because one of our objectives is to accurately predict when and where the rainfall will exceed the threshold. To evaluate whether the nowcast model successfully predicted the occurrence of heavy rainfall just ahead of time, the time at which the threshold was first reached was used as an indicator for verification. For each 500 × 500 m grid square on the forecast grid, we defined \( T_{\text{REF}} \) as the first time when the XRAIN observed that the 10-minute-accumulated rainfall amount exceeded the threshold during the event, and \( T_{\text{NC}} \) was defined as the equivalent time from the prediction. We compared these two parameters by subtracting \( T_{\text{REF}} \) from \( T_{\text{NC}} \). We called this evaluation method “alarm timing evaluation”, because it could address whether an alarm was delivered on time. Figure 9 illustrates the method used to evaluate the alarm timing. Considering that most ETSs are less than 0.2 at lead times of 50 and 60 minutes, only forecasts up to 40 minutes upstream were used, which means that an observation at a certain time was compared with forecasts made at 40, 30, 20, and 10 minutes previously. Grid points covering the whole nowcast domain were categorized into five groups: “HIT” if \( T_{\text{NC}} = T_{\text{REF}} \), “EARLY” if \( T_{\text{NC}} < T_{\text{REF}} \), “LATE” if \( T_{\text{NC}} > T_{\text{REF}} \), “FALSE” if the nowcast predicted a value above the threshold but the observation did not show that value, and “MISS” if the observation exceeded the threshold but the prediction did not.

![Fig. 8. Comparison of ETSs for different rainfall thresholds, for (a) CASE1, (b) CASE2, and (c) CASE3. Solid, cool color lines show the skill for VIL_NC, while dashed, warm color lines show the skill for RR_NC, both measured against XRAIN.](image)

![Fig. 9. Schematic representation of the strategy used to evaluate alarm timing.](image)
“EARLY” was 30 minutes. The results of alarm timing evaluation for a threshold of 5 mm for VIL_NC and RR_NC are shown in Fig. 10. The results obtained using other thresholds are similar to those presented. The VIL_NC scores more HITs than does RR_NC. The percentages of grid points classified as HIT for VIL_NC were 47.2 %, 37.8 %, and 40.1 % in CASE1, CASE2, and CASE3, respectively, and the corresponding values for RR_NC were 22.5 %, 16.9 %, and 32.3 %, respectively. RR_NC produced a majority of LATEs (45.5 %, 53.4 %, and 40.2 % for CASE1, CASE2, and CASE3, respectively) proving again that it is difficult for RR_NC to accurately predict the timing of an initiation event. Another important concern was the proportion and positions of the MISS and FALSE labels, which were typically located close to the boundary of the rainfall field. VIL_NC reduced the percentage of MISS categories relative to RR_NC by 7.4 %, 6.8 %, and 6 % for CASE1, CASE2, and CASE3, respectively, but increased the percentage of FALSE categories by 10.4 %, 12.7 %, and 7.7 %, respectively.

5. Discussion and conclusions

The primary objective of this study was to increase the skill in forecasting imminent LHR in the Kanto region of Japan by using the volume scan observations obtained from the XRAIN X-band polarimetric radar network. The method used in the operational estimation of the liquid water content and VIL from polarimetric radar observations was established, and the VIL_NC model was developed to provide accurate predictions just before the rainfall reached a certain threshold. As explained in Section 3.2, the design of VIL_NC was based on a conceptual model that assumes a steady-state source term and a uniform VIL–R relationship during the nowcast period. Physical interpretation of these variables is difficult because the microphysical processes within the storm are not described. Therefore, instead of discussing the validity of variables and their physical interpretation, the performance of VIL_NC was assessed by comparing the prediction results with accumulated rainfall during each forecast time step as observed by XRAIN and with predictions from RR_NC that adopted the same advection scheme but by using XRAIN rainfall rate as input data. Nowcasting experiments were performed over three precipitation events, two isolated storms and one synoptic event, and a series of thresholds were considered to determine the most efficient application of the model. The performance evaluation emphasized the first prediction; that is, the forecast of rainfall for 10 minutes ahead, for the purpose of imminent warning.

In contrast to earlier research that applied the RadVil model to an LHR event in Tokyo (Ishihara 2013a, b), our findings suggest that VIL_NC may improve the performance of imminent nowcasting. VIL_NC has a tendency to generate spurious additional areas of light rainfall, whereas the RR_NC tends to create more missing grids. From the viewpoint of the timing of severe rainfall warnings, VIL_NC generated more FALSE warnings whereas RR_NC resulted in more MISS categories. Of course, the overestimation tendency of VIL_NC and the underestimation tendency of RR_NC affect the result directly, but the motion vector might also be a contributing factor because both the MISS and FALSE results were located mostly at the edge of the rainfall field. Therefore, modification of the advection vector by introducing a more accurate scheme could lead to improved predictions from both VIL_NC and RR_NC.

Considering the whole precipitation period, the improvement in first predictions, as measured against the XRAIN observations in the statistical sense, was slight for VIL_NC, but the time lags on the initial stage and the peak point of all events in RR_NC were explicitly remedied, as seen in the time series at representative points. The time lag compared with the radar observations for RR_NC was 5–10 minutes, whereas there was little or no time lag for VIL_NC in all three events. Figure 11 shows three-dimensional views of the initial state of each event and helps to explain why VIL_NC is able to accurately predict rainfall before it begins near the ground level. In Fig. 11a, at 1530 JST in CASE1, no rain could be identified from the XRAIN map at the representative point, so no rainfall could be predicted if only near-surface information was used. However, the volume scan detects raindrops that are aloft. These raindrops can at first be called “eggs” of rain, and they contribute to the accurate predictions made by VIL_NC for the next 10 minutes. In CASE2, the rainfall field arrives at the representative point at 1439 JST, which is 1 minute earlier than the time shown in Fig. 11b, and indeed, the strong rainfall area is still some distance from the point at 1440 JST. However, the convection cell tilts toward the direction of the point such that a strong “core” (> 2 g m⁻³) is present directly above the point at a height of 4–6 km. Vertical wind shear could have been the principal cause of this tilting because the core was tilting forward; i.e., in the direction of the cell movement. VIL_NC uses the information from the upper core, resulting in the accurate prediction for 1450 JST. On
Fig. 10. Comparison of the time at which the threshold is reached, for 10-minute rainfall amounts, between the first nowcast prediction (10 minutes ahead) and the XRAIN observations. Left column shows VIL_NC and right column shows RR_NC results. (a, a’): CASE1; (b, b’): CASE2; (c, c’): CASE3. Shading is green for predictions and observations reaching the threshold (5 mm) at the same time, warm colors (yellow to red) for predictions later than observations, cold colors (blues) for predictions earlier than observations, and gray for nowcast predicting a value above the threshold when observations were below the threshold.
the other hand, RR_NC tends to underestimate the rainfall at 1450 JST (see Fig. 7). The differences between VIL_NC and RR_NC on 26 August (CASE3, Fig. 11c) were also caused by an upper-level “core”. The horizontal movement of the rainfall field in this case was more rapid than in the other two cases (i.e., about 2.5 m s^{-1} in this case, but less than 1 m s^{-1} in the others, which were calculated as the movement vector from two consecutive 10-minute accumulated rainfall images). In addition, the vertical wind shear was stronger than in CASE2 (the difference in the radar-observed horizontal wind velocity estimated from CAPPI data between 5 km and 1 km was about 8.4 m s^{-1} in CASE3, whereas it was 2.5 m s^{-1} in CASE2), which results in an even larger time gap between the observations and the RR_NC predictions. The three-dimensional precipitation cloud structures suggested that the reduced time lag associated with VIL_NC was achieved partly because VIL_NC successfully captured “eggs” of rain formed aloft and “cores” brought in by vertical wind shear during the precipitation events. This also implies that VIL_NC could effectively predict the initial stage of the precipitation events even for synoptic-scale phenomena, although more validation experiments will be needed if we are to generalize this finding. In addition, RR_NC tends to underestimate rainfall whereas VIL_NC tends to overestimate rainfall. Therefore, it is possible that VIL_NC could play a supporting role in hydrological applications that make use of VIL_NC predictions as maximum rainfall.

Considering the advection scheme used, we were not surprised to find that the forecast skill decreased rapidly with increasing lead time. The ETS dropped below 0.3 for all thresholds at lead times greater than 40 minutes in both VIL_NC and RR_NC. Increasing the threshold also resulted in a decrease in the forecast skill, which was consistent with previous studies.
Considering the low ETS values (< 0.5) at thresholds of 8 and 10 mm, we recommend that a threshold of less than 5 mm be used for a 10-minute rainfall to maximize the forecast skill. Based on the three precipitation events analyzed in this study, the VIL_NC model has been proved to be more robust for the two isolated cases (CASE1, 2), and the VIL_NC model is comparable with RR_NC for the synoptic case (CASE3) except when evaluating the forecasts using 1 mm 10-minute rainfall threshold.

Our most important finding is that VIL_NC is suitable for use as an indicator or alarm system for heavy rainfall that might affect daily public activities, although more cases must be studied to quantitatively evaluate the performance of VIL_NC. A comparison with the ground-observed data will also be necessary to generalize this finding since the precipitation observed by XRAIN may differ from the ground-based rain gauge observations. For the three cases studied here, VIL_NC performed significantly better than RR_NC by correctly capturing the time at which thresholds were first exceeded at a majority of grid points from a nowcast made 10 minutes previously, whereas RR_NC produced a much greater number of delays and misses. As the intensity of LHR can increase from zero to more than 100 mm h−1 within 20 minutes over a very small area, this 10-minute lead time is of interest to both those engaged in daily activities and emergencies or public safety concerns. Nevertheless, the existence of missed precipitation cells and false alarms at some grid cells raises the possibility of improving the forecast score by introducing a better advection vector method, such as the tracking method.

The observational tracking of storms has been improved through numerous studies (e.g., Turner et al. 2004; Van Horne et al. 2006), making it possible to extend the upper limit of the nowcast prediction. As the VIL_NC model operates by separating the advection estimation and persistence development into individual parts with a predetermined advection velocity applied to the persistence of variables, the forecasting skill of the current VIL_NC model can be improved by simply substituting in a more sophisticated advection scheme. It is also possible, with some modifications, to use multi-scale advection velocities. However, we must point out that accurate motion calculations are more time-consuming; consequently, improved tracking might cause a concomitant reduction in the lead time.

Overall, the present results suggest that VIL_NC can improve the timing of alarm notifications and show forecasting skills equal to or better than those of RR_NC. However, as the peak timing, forecast skill score, and threshold dependence varied among the three precipitation events, a comprehensive verification should be undertaken to properly assess the performance of VIL_NC. Moreover, only three case studies were introduced in this study; additional case studies are required to generalize these findings. To this end, a follow-up project, based on a social experiment involving 2000 volunteers, has been carried out, and the upcoming results should enable a more comprehensive evaluation of VIL Nowcast.

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