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4DDA OF RADAR ECHO AND DOPPLER VELOCITY BY AN ATMOSPHERIC MODEL WITH A CONCEPTUAL PRECIPITATION MODEL

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Four dimensional data assimilation (4DDA) system of three-dimensional distributions of radar reflective factor and Doppler velocity by a hydrostatic atmospheric model with a conceptual precipitation model will be proposed. The 4DDA is realized by the variational method for Doppler velocity and the extended Kalman filter for radar reflective factor. The method was applied to a rainfall event observed by two neighboring operational volume-scanning radars one of which is the Doppler radar. As a result, it was found that introducing such the assimilation method improves the prediction accuracy of three hours lead time. However, a limitation of used hydrostatic mesoscale model was also found. In the initial condition after assimilation, there is a little heavy rainfall area at the position different from radar observation. This shows that there is a discrepancy between the time evolution of observations and the time evolution that governing equations of the used model requires.

Key Words **:** *rainfall prediction, weather radar, Doppler radar, data assimilation,, 4DDA, short-term rainfall prediction, Kalman filter, conceptual rainfall model, mesoscale model*

1. INTRODUCTION

Nakakita et al.[1)] classified operational short-term rainfall prediction into three categories: (1) those that extrapolate movement pattern of a horizontal rainfall distribution; (2) those that use the principles of water balance and thermodynamics with a conceptual precipitation method; and (3) those that use the full set of conservation equations at the mesoscale. Full list of related research paper is shown in Sugimoto et al.[2)]. Most of the short-term rainfall prediction methods that use radar information have been belonged to the first category. It is apparent, however, that the temporal variation of the rainfall distribution is excessively complicated to be expressed by such simple extrapolation methods, especially over mountainous regions.

The method belonging to the first category can practically be used until only one-hour prediction lead-time. On the other hand, a method belonging to the second category was developed by Nakakita et al.[1)] and this is operationally used by the Kinki Branch of the Ministry of Land, Infrastructure and Transportation (MLIT), Japan. On the other hand, in the last decade, as a method belonging to the third category, Japan Meteorological Agency started forecasting service based on a non-hydrostatic mesoscale numerical model. Also, mesoscale numerical prediction system with non-hydrostatic assumption, such as RAMS, ARPS, MM5, CReSS and WRF, has been developed. Recent concern in the community of meteorology is the assimilation of information from weather radar and other remote sensing, with these mesoscale numerical models for providing more accurate initial condition in a smaller spatial scale. The ultimate methodology of the data assimilation would be the four dimensional data assimilation (4DDA).

Under these circumstances, the main concern of this paper is to develop a basic method of 4DDA of radar reflective factor and Doppler velocity. Therefore, used mesoscale atmospheric model in this paper is a hydrostatic model developed by authors who know all the details in this model and computer codes.

2. USED MESOSCALE MODEL

As mentioned above, the atmospheric model used is a hydrostatic mesoscale model. The model is developed by adding momentum conservation equations to a model that is used in the prediction method by Nakakita et al.[1]. Hereafter, the prediction method without momentum equation is referred as the original prediction method.

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(1) Outline of the original prediction method

This rainfall prediction method is a physically based, short-term rainfall prediction model. The basic equations used in the physically based model are sets of partial differential equations for conservation of liquid water, heat and water vapor at the mesoscale, and an equation for estimating the rainfall intensity. These equations are written as

$$\frac{\partial m_l}{\partial t}+u\frac{\partial m_l}{\partial x}+v\frac{\partial m_l}{\partial y}+w\frac{\partial m_l}{\partial z}=\frac{Q}{\rho}+\frac{\rho_w}{\rho}\frac{\partial r}{\partial z} \tag{1}$$

$$\frac{\partial \theta}{\partial t}+u\frac{\partial \theta}{\partial x}+v\frac{\partial \theta}{\partial y}+w\frac{\partial \theta}{\partial z}=\frac{LQ}{\rho}\left(\frac{1000}{p}\right)^{R_d/C_p} \tag{2}$$

$$\frac{\partial m_v}{\partial t}+u\frac{\partial m_v}{\partial x}+v\frac{\partial m_v}{\partial y}+w\frac{\partial m_v}{\partial z}=-\frac{Q}{\rho} \tag{3}$$

$$r=-\frac{\rho}{\rho_w}W_t m_l \tag{4}$$

where, x, y, and z define Cartesian coordinates in two horizontal direction and the vertical, respectively; u, v, and w are velocities of the air in the x-, y-, and z- directions in m/s; m_l is the mixing ratio of precipitation particles in kg/kg; m_v is the mixing ratio of water vapor in kg/kg; θ is the potential temperature in K; Q is the conversion rate of water vapor (CRWV) in kg/m^3/s; r is the rainfall intensity in m/s; L is the latent heat of vaporization in J/kg; C_p is the specific heat at constant pressure in J/K/kg; p is the air pressure in hectopascals; W_t is the relative fall velocity of water particles in m/s; ρ and ρ_w are the density of air and liquid water in kg/m^3, respectively. The CRWV is defined as the amount of water vapor converted to precipitation particles in per unit time and unit volume. There is no provision for cloud particles because they cannot be detected by weather radar. The terminal velocity W_t is from Ogura and Takahashi[3]; it relates the water content of the air to the mean volume-weighted terminal velocity. These basic equations are transformed from Cartesian coordinates (x, y, z) into a terrain-following coordinate system (x, y, s). The transformation can be written as $s = (z - h(x, y))/(H - h(x, y))$, where, H is the elevation of the top grid point in the model and $h(x, y)$ is the terrain elevation.

This prediction method involves several steps that are presented in more detail in Nakakita et al.[1]. Here, only important parts that relate to the data assimilation are described as followed.

a) Estimation of initial conditions

GPV and AMeDAS data with meso-α scale resolution are used to estimate three-dimensional wind vector (u, v, w), the air temperature, air pressure, and water vapor field under the constraint of hydrostatic. The estimated wind and pressure fields are assumed to be constant during the prediction procedure and are used as initial values. When introducing momentum conservation equations, this assumption will be renounced and all the fields will be time updated.

An important part of this method is estimating the three-dimensional distribution of CRWV Q on the meso-β scale using Eq. (1) based on the retrieval method proposed by Nakakita et al.[4]. Here, using Marshal and Palmer's drop size distribution[5] for rain and Gunn and Marshall's[6] for snow, the past and current three-dimensional distribution of rainfall intensity r and the mixing ratio of precipitation particles m_l are estimated from three-dimensional distribution of radar reflective factor Z. Then the CRWV can be estimated using Eq. (1) because (u, v, w), m_l and r have been already estimated. In other words, the past and current CRWV distributions can be estimated using the past and current radar-reflectivity distributions. Additionally, the three-dimensional distributions of θ and m_v at the scale of Q are retrieved with identifying the model parameter described in **b)**, using the conservation equations.(1)–(3) and both CRWV and (u, v, w).

b) Conceptual precipitation model and prediction procedure

The conceptual precipitation model can be described by

$$-\frac{Q}{\rho}=-\frac{d}{dt}((1-\alpha(x,y,z))m_s),\ \text{if}\ m_v \geq (1-\alpha)m_s \tag{5}$$

and $\alpha(x, y, z)$ is the model parameter to be identified and predicted. Additionally, m_s is the saturation mixing ratio, which can be identically calculated from the potential temperature θ and the air pressure p using any formula.

Eq. (5) implies the assumption that water vapor beyond a newly defined saturation mixing ratio, $(1-\alpha)m_s$ condenses to precipitation particles (or precipitation particles evaporate when water vapor mixing ratio is less than $(1-\alpha)m_s$). In other words, domains with large values of the parameter α are prone to relatively heavy rainfall. Therefore, the parameter can be taken as a kind of index which shows the degree of shortage of vertical water vapor flux brought on by the used meso-α wind field (u, v, w). In this sense, the conceptual precipitation model plays the role of bridging the gap between radar information and GPV scales.

The past and current three-dimensional distributions of the parameter α are identified using Eq.(5) with estimated three-dimensional distribution of CRWV Q. On the other hand, in the prediction procedure, the three-dimensional distribution of the parameter α is calculated by simple horizontal advection of the identified distribution of α. That is

$$\frac{\partial \alpha}{\partial t}+U\frac{\partial \alpha}{\partial x}+V\frac{\partial \alpha}{\partial y}=0. \tag{6}$$

An advection vector (U, V) of the parameter is determined using an advection model proposed by Shiiba et al.[7]. The use of (U, V) instead of (u, v) is intended for expressing propagation of meso-β scale perturbation that drives the heavier rainfall field.

Then, after basic equations (1)-(4) are simultaneously integrated, the three-dimensional distribution of rainfall intensity r can be predicted.

(2) Introducing momentum conservation equations

In the original prediction method described above, the estimated wind and pressure fields are assumed to be constant during the prediction procedure. However, those fields should be updated so that 4DDA of Doppler velocity could be introduced into the original prediction method. Therefore, a hydrostatic atmospheric numerical model developed by Nakakita et al.[8] is combined with the original prediction model. The momentum conservation equations used in the numerical model are

$$\begin{aligned}\frac{du}{dt}= & -\theta_0\frac{\partial \pi'}{\partial x}+(1-s)\frac{\theta'}{\theta_0}g\frac{\partial h}{\partial x}+s\frac{\theta'}{\theta_0}g\frac{\partial H}{\partial x}\\ & +f(v-v_{g0})+\frac{1}{\rho_0(H-h)^2}\frac{\partial}{\partial s}(\rho_0 K\frac{\partial u}{\partial s}),\end{aligned} \tag{7}$$

$$\begin{aligned}\frac{dv}{dt}= & -\theta_0\frac{\partial \pi'}{\partial y}+(1-s)\frac{\theta'}{\theta_0}g\frac{\partial h}{\partial y}+s\frac{\theta'}{\theta_0}g\frac{\partial H}{\partial y}\\ & -f(u-u_{g0})+\frac{1}{\rho_0(H-h)^2}\frac{\partial}{\partial s}(\rho_0 K\frac{\partial v}{\partial s}),\end{aligned} \tag{8}$$

with the hydrostatic assumption

$$\frac{\partial \pi'}{\partial x}=-\frac{\theta'}{\theta_0^2}g\left(H-h\right), \tag{9}$$

where, g is the global average of gravity acceleration in m/s^2; π is a normalized air pressure defined by C_pT/θ in J/K/kg; T is the air temperature in K; f is the Coriolis parameter in 1/s; (u_g, v_g) is the geostrophic wind vector in m/s; K is the eddy diffusion coefficient in ms. Details on definition of K can be seen in Nakakita et al.[8]. Subscript 0 denotes the layer averaged value and dash denotes the deviation from the layer averaged value.

Moreover, the elevation of the top grid point H is assumed to correspond to a constant-pressure level and to depend on position and time. Under these assumptions, the equation of continuity in the anelastic type can be written as

$$\begin{aligned}&\frac{\partial(\rho_0 u)}{\partial x}+\frac{\partial(\rho_0 u)}{\partial y}+\frac{\partial(\rho_0 \omega)}{\partial z}\\ &\quad =-\frac{1}{H-h}\left(\frac{\partial(\rho_0 s)}{\partial s}+u\frac{\partial(H-h)}{\partial x}+v\frac{\partial(H-h)}{\partial y}\right)\end{aligned} \tag{10}$$

with

$$\omega\equiv\frac{ds}{dt}=\frac{\partial s}{\partial t}+u\frac{\partial s}{\partial x}+v\frac{\partial s}{\partial y}+w\frac{\partial s}{\partial z}. \tag{11}$$

Final, by vertically integrating the continuity equation (10), we can get

$$\begin{aligned}&\frac{\partial H}{\partial t}=\\ &-\frac{1}{\rho_0(H)}\int_0^1\left[\frac{\partial}{\partial x}\left\{\rho_0 u(H-h)\right\}+\frac{\partial}{\partial y}\left\{\rho_0 v(H-h)\right\}\right]ds\end{aligned} \tag{12}$$

as the equation of the time change of the top elevation H.

In the prediction procedure, Eqs.(1)-(12) are simultaneously integrated using the Matsuno scheme[9] and the upstream scheme. Details on boundary conditions can be seen in Nakakita et al [8].

3. 4DDA OF DOPPLER VELOCITY AND RADAR REFLECTIVE FACTOR

(1) Strategy of four dimensional data assimilation

Roughly speaking, the data assimilation is the procedure of finding out an optimal initial condition by minimizing a weighted sum of residuals between the model outputs and their observations of the outputs, and residuals between the model out puts and its background estimates by, say, a priori forecast. In general, an initial condition is determined so that a cost function defined as

$$\begin{aligned}J(\mathbf{x})=&\frac{1}{2}(\mathbf{y}-H(\mathbf{x}))^T R^{-1}(\mathbf{y}-H(\mathbf{x}))\\ &+\frac{1}{2}(\mathbf{x}-\mathbf{x}_b)^T B^{-1}(\mathbf{x}-\mathbf{x}_b)+J_c(\mathbf{x})\end{aligned} \tag{13}$$

should be minimized. Here, $\mathbf{x}$ is a vector of predictive variables of all the model grid points; $\mathbf{x}_b$ is the back ground estimate of $\mathbf{x}$; B is the covariance matrix of expected error of $\mathbf{x}_b$; $\mathbf{y}$ is the vector of observations (e.g. radar observation); $H(\mathbf{x})$ is the observation operator; R is the covariance matrix of expected error of observations; $J_c(\mathbf{x})$ is an additional penalty function through which other dynamical or physical constraints can be imposed.

The four dimensional data assimilation (4DDA) is the procedure of globally minimizing $J(\mathbf{x})$ through all the predictive variables during whole the assimilation time period, under the constraint of prognostic and diagnostic governing equations

$$\frac{d\mathbf{x}}{dt}=\mathbf{M}(\mathbf{x}). \tag{14}$$

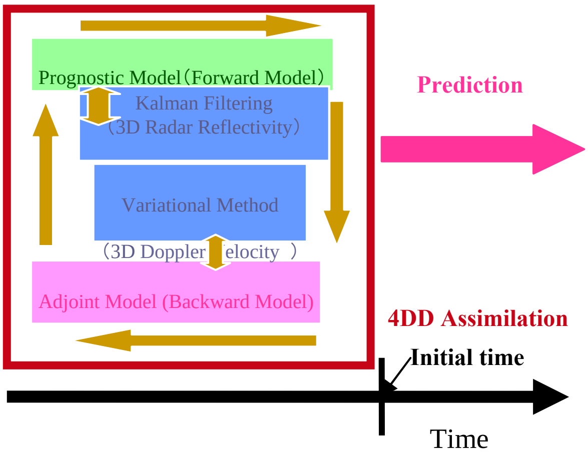


Fig. 1 Strategy of 4DDA

Fig. 1 schematically shows the strategy of 4DDA procedure proposed in this paper. The variational method is used for the assimilation of the Doppler velocity and the extended Kalman filter is used for the assimilation of the radar reflectivity.

(2) Assimilation of radar reflectivity with the extended Kalman filter

Eqs. (1), (5), and (6) with random error v_m, v_Q, and v_α, are chosen as the "system equations" as well as Ogura and Takahashi's relation[2] with random error v_W; $W_t = K_w m_l^{\beta_W} + v_W$. Therefore, m_l and α are taken as the state variables. On the other hand,

$$Z = a m_l^{\ b} + w_Z \tag{15}$$

is chosen as an "observation equation". Here, Z is the observation variable as the radar reflective factor and w_z is a random error. In order to get Eq. (15), ether the radar equation, or Marshal and Palmer's drop size distribution for rain and Gunn and Marshall's can be used, with Eq. (4). Moreover, $\alpha_{\mathrm{obs}} = \alpha + w_\alpha$ is chosen as another "observation equation". Here, α_{obs} is also taken as an observation variable which can be directly estimated through Eq. (5) with CRWV Q directly estimated through Eq. (1) from radar observations. w_α is a random error.

An important thing is that the Kalman filtering theory can be derived under the condition that $M(\mathbf{x})$ and $H(\mathbf{x})$ are linear in terms of $\mathbf{x}$ and $\mathbf{y}$. Therefore, $M(\mathbf{x})$ and $H(\mathbf{x})$ have to be linearized, and the Kalman filter with these linearizations is called the extended Kalman filter. In this paper, $M(\mathbf{x})$ and $H(\mathbf{x})$ are linearized by Taylor's expansion. On the other hand, if we assume that Z' defined by $Z^{1/b}$ is a direct observation from radar, Eq. (15) is reduced to $Z' = a' m_l$. without using the Taylor's expansion.

(3) Assimilation of Doppler velocity with the variational method

In the assimilation of Doppler velocity, the cost function is formulated as

$$\begin{aligned} J(\mathbf{x}) = \frac{a_w}{2}\sum_{k=0}^{N}(\mathbf{y}_{k,\mathrm{obs}} - H_k(\mathbf{x}_k))^T R_k^{-1}(\mathbf{y}_{k,\mathrm{obs}} - H_k(\mathbf{x}_k)) \\ + \frac{1}{2}(\mathbf{x}_0 - \mathbf{x}_{o,\mathrm{b}})^T B^{-1}(\mathbf{x}_0 - \mathbf{x}_{0,\mathrm{b}}), \end{aligned} \tag{16}$$

under the constraint of discretized governing equation

$$\mathbf{x}_{k+1} = \mathbf{x}_k + \mathbf{M}(\mathbf{x}_k)\Delta t. \tag{17}$$

Here, the second term of Eq. (16) is evaluated by the second term of Eq. (13) because all $\mathbf{x}_k$ and $\mathbf{x}_{k,\mathrm{b}}$ are determined by $\mathbf{x}_0$ through the equation (14).

On the other hand, the relative weight α_w between first and second terms in the Eq. (16) can be determined so that the Akaike's Bayesian Information Criteria (ABIC) should be minimized under the given derivative of operator $\partial H_k(\mathbf{x})/\partial \mathbf{x}$ and the covariance matrixes R_k and B.

The purpose of the variational method is to find out $\mathbf{x}_0$ that minimizes the cost function $J(\mathbf{x}_0)$ defined by Eq.(16) under the constraint of Eq.(17) and observations $\mathbf{y}_{k,\mathrm{obs}}$. This is identical to minimizing

$$L(\mathbf{x},\boldsymbol{\lambda}) = J(\mathbf{x}) + \sum_{k=0}^{N}\boldsymbol{\lambda}_k^T(\mathbf{x}_k - \mathbf{x}_{k-1} - M(\mathbf{x}_{k-1})\Delta t) \tag{18}$$

by the method of Lagrangean undetermined coefficients. Here, T denotes the operation of transposition, and $\boldsymbol{\lambda} = (\lambda_1, \lambda_2, .., \lambda_N)$ is called the Lagrangean undetermined coefficients to be determined as well as optimal estimates of $\mathbf{x}_1$, $\mathbf{x}_2$, …, $\mathbf{x}_N$. This can be realized by $\partial L/\partial \mathbf{x}_k = 0$, $\partial L/\partial \boldsymbol{\lambda}_k = 0$.

These equations determine $\boldsymbol{\lambda}$ by the time-step procedures

$$\boldsymbol{\lambda}_k = \begin{cases} 0, \ (k = N+1), \\ (I + \mathbf{M}_k^T\Delta t)\boldsymbol{\lambda}_{k+1} - H_k^T R_k^T(H_k(\mathbf{x}_k) - \mathbf{y}_{k,obs}), (0 \le k \le N). \end{cases} \tag{19}$$

This equation is called as the "adjoint equation", and $\boldsymbol{\lambda}$ is called as the "adjoint variable". You can see that the adjoint equation should be solved backward, because the subscript of $\boldsymbol{\lambda}$ is k in the left hand side while it is k+1 in the right hand side. This is the reason why the adjoint model is called the backward model as shown in Fig. 1. Assuming that $\mathbf{x}_o$ and $\boldsymbol{\lambda}_o$ are obtained by (18) and (19), we can get gradient of the cost function $J(\mathbf{x})$ as

$$\nabla J(\mathbf{x}) = \alpha_w B^{-1}(\mathbf{x}_0 - \mathbf{x}_0^b) - \boldsymbol{\lambda}_0. \tag{20}$$

Once we get this estimation of the gradient of $J(\mathbf{x})$, we can get the optimal $\mathbf{x}$ using any methods of optimization. In this paper, the conjunct gradient method is used.

As the governing equations that become the constraint as Eq. (17), momentum conservation equations (7) and (8) are selected as the most basic equations. Also, Eq. (2) under the constraint of Eq.

(9) is also selected, because θ' directly affects the momentum conservation equations (7) and (8).

Note that the backward Eq. (19) should be discretized as completely as possible following to the forward Eq.(17) which is also discretized by finite discrete approximation. In this paper, the Matsuno scheme is used for time integration and the typical upstream scheme is used for advection term in the forward model. Another important thing is how to define **y** and $H(\mathbf{x})$. Here, we defined $H(\mathbf{x})$ as the Doppler velocity at grid point (x, y, z). That is,

$$H(u,v,w) = u\sin\phi\cos\varphi + v\cos\phi\sin\varphi + (w - W_t)\sin\phi \qquad (21)$$

here, ϕ is the elevation angle and φ is the azimuth of the radar beam. On the other hand **y** is obtained after vertically interpolating the Doppler velocities observed at just above and below the simulation grid points. The interpolation is done as a vector that has the beam direction.

4. CASE STUDY AND DISCUSSIONS

Fig. 2 shows the target area with the size of 234 km times 351 km. The circles with the radius of 120 km show the observation areas of two operational volume-scanning radars managed by the MLIT. The radar located at northern part is a Doppler radar and the other is a conventional radar. The upper limit of the observation domains is 15 km from sea level and volume scan is carried out with every 7 minutes. In the data assimilation and prediction procedures, the coordinate system is a terrain-following in a three-dimensional geometry with 20 layers and with horizontal grid spacing of Δx, Δy = 9 km. Also, the 200 hPa level is used as the constant-pressure top boundary.

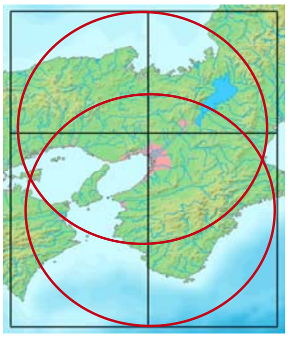


Fig. 2 Target area.

After applications with Eq. (5), the conceptual precipitation model has been replaced by

$$-\frac{Q}{\rho}(1-\alpha)^{-2} = -\frac{d}{dt}((1-\alpha(x,y,z))m_s),\ \text{if}\ m_v \geq (1-\alpha)m_s \qquad (22)$$

so that heavy rainfall prone effect by this model should be suppressed than original prediction method. The reasons of this are: i) there is no strong horizontal convergence in the original prediction method because the used wind field is in meso-α scale and is assumed to be constant, ii) However, in this paper, the field is not assumed to be constant and some strong convergences would be generated through both assimilation and prediction procedures.

Table 1 Observed, assimilated, and predicted rainfall intensity

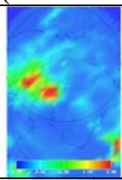
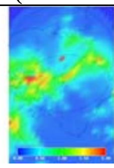
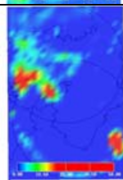
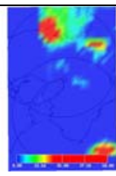
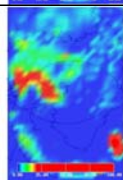
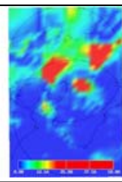
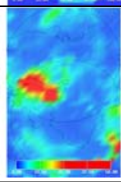
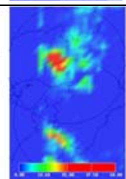
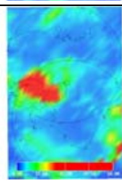
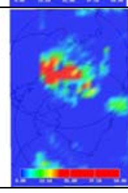
	Initiatl Time (Assimilated)	3-hours ahead (Prediction)
(A) Observed Rainfall		
(B) Without Data Assimilation		
(C) Only Variational Method (Doppler Velocity)		
(D) Only Kalman Filter (Radar Reflective Factor)		
(E) Both Variational Method and Kalman Filter		

Table 1, (B) shows rainfall intensity predicted by original prediction method with the modified conceptual precipitation model. Therefore, the data assimilation is not used. On the other hand, **(C)** and **(E)** show assimilated and predicted distributions at 3.5 km height. As the time period of assimilation procedure, 30 minutes is used as an arbitrary selection.

In the case without data assimilation, **Table 1,(B)** shows the heavy rainfall area moved far northeast compared to observations in **(A)**, and is subdivided into two parcels. Also, the rainfall in the initial time is not so widely distributed compared to **(A)**.

On the other hand, **Table 1, (C)** shows that, in the case of only the variational method, the northeastward movement of the rainfall area is suppressed compared to **Table 1, (B)**. Also, the assimilated initial rainfall is distributed a little wider than that in **(B)**. **Fig. 3** shows predicted horizontal wind field at 3.5 km height. We can see that gradually increasing northern wind is predicted in the northwest part of the target region, which may decrease the northeastward propagation of rainfall area. However, the rainfall area is still subdivided.

Table 1, (D) shows that, in the case only the Kalman filter is used, the northeastward movement of the rainfall area is suppressed compared to **(B)**, and it is no more subdivided. **Fig. 3** shows that gradually increasing horizontal convergence is predicted. Moreover, we can guess predicted northern wind in the case of only the variational method is directly induced by the assimilated Doppler velocity, while the convergence in the horizontal wind field in the case of only the Kalman filter is indirectly induced by upper wind additionally generated heat release by modified estimates of CRWV *Q* under assimilated radar reflective factor. We can see that widely spread light rain field is reproduced in the assimilated initial rainfall distribution compared to **(B)** and **(C).**

Final, **Table 1, (E)** shows results through data assimilation both by the variational method and the Kalman filter. The northeastward movement is suppressed and the shape is kept better than previous three cases. Also, widely spread light rain field is reproduced in the assimilated initial rainfall distribution compared to **(B)** and **(C).**

However, there exists a relative heavy assimilated rainfall area in the southwest part of the target area in **(E)**, while not so strong rainfall area can be seen in the observed distribution in **(A).** Namely assimilated rainfall intensity in **(E)** is relatively heavier than that of other cases including the observations shown in **(A)**. Note that this is a result from that here is a discrepancy between the time evolution of observations and the time evolution that governing equations of the used model requires. In other words, the existence of the assimilated rainfall area shows us a kind of limitation of the used hydrostatic mesoscale model.

5. CONCLUSIONS

Four dimensional data assimilation (4DDA) system of three-dimensional distributions of radar reflective factor and Doppler velocity by a hydrostatic atmospheric model with a conceptual precipitation model was proposed. The 4DD assimilation was realized by the variational method for Doppler velocity and the extended Kalman filter for radar reflective factor. The assimilation of the Doppler velocity improved three hours ahead prediction of location of heavy rainfall while the assimilation of radar reflective factor reproduced widely spread light rain field. However, a limitation of used hydrostatic mesoscale model was found. In the initial condition after assimilation, there is a little heavy rainfall area at the position different from radar observation. This shows that there is a discrepancy between the time evolution of observations and the time evolution that governing equations of the used model requires. In this sense, it should be a next step that this atmospheric model would be replaced by the CReSS or some other non-hydrostatic mesoscale atmospheric models.

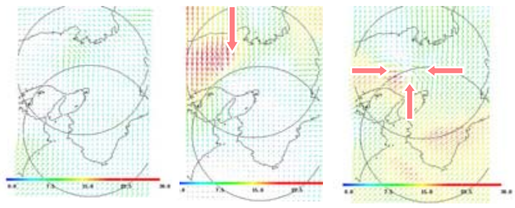


Fig. 3 Predicted wind field at 3.5 km. (3 hrs ahead).

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