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GSMaP RIKEN Nowcast: Global precipitation nowcasting with data assimilation

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Abstract

Since January 2016, RIKEN has been running an extrapolation-based nowcasting system of global precipitation in real time. Although our previous paper reported its advantage of the use of data assimilation in a limited verification period, long-term stability of its forecast accuracy through different seasons has not been investigated. In addition, the algorithm was updated seven times between January 2016 and March 2018. Therefore, this paper aims to present how motion vectors can be derived more accurately, and how data assimilation can constrain an advection-diffusion model for extrapolation stably for the long-term operation. The Japan Aerospace Exploration Agency’s Global Satellite Mapping of Precipitation (GSMaP) Near-Real-Time product is the only input to the nowcasting system. Motion vectors of precipitation areas are computed by a cross-correlation method, and the Local Ensemble Transform Kalman Filter generates a smooth, complete set of motion vectors. Precipitation areas are moved by the motion vectors up to 12 hours, and the product, called “GSMaP RIKEN Nowcast,” is disseminated on a webpage in real time. Most of the algorithmic updates were related to better estimating motion vectors, and the forecast accuracy was gradually and consistently improved by these updates. Particularly, the threat scores increased the most around 40°S and 40°N. A performance drop in the northern hemisphere winter was also reduced by reducing noise.
in advection. The time series of ensemble spread showed that an increase in
the number of available motion vectors by a system update led to a decrease
in the ensemble spread, and vice versa.
1. Introduction

Short-term prediction of precipitation is of great interest for various purposes such as disaster prevention, agriculture, economy, and daily life. Ground-based precipitation observations such as weather radar and gauge networks provide accurate and timely information. However, sparsely observed areas such as developing countries and ocean basins suffer from water-related disasters partially due to the lack of information. Satellite observations are a powerful tool over these areas. Satellite-borne precipitation radars such as the Tropical Rainfall Measuring Mission (TRMM) Precipitation Radar (PR) (Kozu et al., 2001; Iguchi et al., 2009) and the Global Precipitation Measurement (GPM) Dual-frequency Precipitation Radar (DPR) (Kojima et al., 2012; Seto and Iguchi, 2015) are useful for global quantitative precipitation estimation, but their spatiotemporal coverage is limited. Therefore, passive microwave observations and infrared observations are the main sources of near-real-time precipitation information, and passive microwave rainfall algorithms have been improved using TRMM PR and GPM DPR.

Using microwave observations from the GPM Microwave Imager (GMI) on the GPM core observatory and other microwave sensors of the GPM con-
stellation partners, near-real-time satellite-based products are distributed: the Japan Aerospace Exploration Agency (JAXA) Global Satellite Mapping of Precipitation (GSMaP; Kubota et al., 2007; Ushio et al., 2009) and the National Aeronautics and Space Administration (NASA) Integrated Multi-satellite Retrievals for GPM (IMERG; Huffman et al., 2018).

For real applications, short-term predictions will also be useful. Ground-based radar precipitation nowcasting has a long history (e.g., Rinehart and Garvey, 1978; Dixon and Wiener, 1993; Bowler et al., 2006), whereas satellite-based global precipitation nowcasting is a relatively new area. Recently, Otsuka et al. (2016a) developed a global precipitation nowcasting system using GSMaP, and the system is running at RIKEN in real time since January 2016 (GSMaP RIKEN Nowcast, hereafter RNC). The predictions are made open to public under the permission by the Japan Meteorological Agency (JMA) as required by the Japanese law. Although Otsuka et al. (2016a) presented the initial verification results for a particular month, its long-term stability in different seasons has not been investigated yet. Our real-time operations for more than two years revealed its advantages and limitations on longer time scales. The lessons learned from the real-time operations motivated us to update the system to improve its accuracy and computational performance.

This paper aims to describe the verification results for the period from
January 2016 to March 2018 including the impact of each algorithm update. The key questions here are: 1) how motion vectors for extrapolation can be derived more accurately, and 2) how an advection-diffusion model for extrapolation can be stably constrained by data assimilation. The first question will contribute to a better implementation of motion tracking techniques, whereas the latter will lead to better handling of uncertainties in data assimilation. The paper is organized as follows. Section 2 introduces the system design, Section 3 shows the verification results, Section 4 provides discussion, and Section 5 summarizes the paper. Some of the system details will be described in Appendix.

2. Methodology

2.1 Overview

The workflow of the system is as follows (Fig. 1).

1. Data transfer of GSMaP from JAXA to RIKEN

2. One-hour ensemble forecast of motion vectors \( \mathbf{u} \) from time \( t - 1 \) to 
   \[ t: \mathbf{u}_{t-1}^{a,m} \rightarrow \mathbf{u}_t^{f,m}, \] where superscript \( f, a, \) and \( m \) represent forecast, analysis, and ensemble member, respectively
3. Motion vector computation \((\mathbf{u}^o_t)\) using GSMaP Near-Real-Time (NRT) images at time \(t - 1\) and \(t\) (denoted as NRT\(_{t-1}\) and NRT\(_t\))

4. Ensemble Kalman filter using \(\mathbf{u}_{f,m}^t\) and \(\mathbf{u}^o_t\) to obtain analysis ensemble-mean motion vectors \(\overline{\mathbf{u}}^o_t\) and analysis ensemble \(\mathbf{u}^{a,m}_t\)

5. Deterministic 12-hour forecast of precipitation from time \(t\) to \(t + 12\) (RNC\(_{t+12}\)) using \(\overline{\mathbf{u}}^o_t\) and NRT\(_t\) as the initial condition

6. Visualization

7. Visual inspection by a licensed forecaster

8. Dissemination at RIKEN’s webpage and JAXA’s webpage

Running an operational system helps finding key issues for future research directions. This includes an end-to-end workflow such as data transfer, computational cost, visualization, and dissemination to end users. For this purpose, GSMaP RNC forecasts are made readily available to public in real time at https://weather.riken.jp/ as a part of our research activities. See Appendix A for more information.

2.2 Data and algorithm

Here is a brief summary of the system. Refer to Otsuka et al. (2016a,b) for details. The input to the system is GSMaP NRT algorithm version 6
(Ushio et al., 2009; Ushio and Kachi, 2009; Kachi et al., 2011) rain rate at
0.1° × 0.1° resolution from 60°S to 60°N. NRT is available every hour, after
four hours from the end of one-hour observation time window. The motion
vectors of NRT rain fields are computed by a variant of the Tracking Radar
Echoes by Correlation (TREC; Rinehart and Garvey, 1978).

To obtain a smooth, complete set of motion vectors from noisy TREC-
based motion vectors, the Local Ensemble Transform Kalman Filter (LETKF;
Hunt et al., 2007; Miyoshi and Yamane, 2007) is used with 20 ensemble mem-
ers. The covariance localization function is a Gaussian with the length
scale of 100 km, and the covariance inflation method is a multiplicative
inflation with a factor of 1.01 simultaneously with the relaxation to prior
spread (Whitaker and Hamill, 2012) so that the ensemble spread does not
change in time (Otsuka et al., 2016a).

The prediction model is an advection equation with a divergence damp-
ing term. The time integration method is the second-order Adams-Bashforth
scheme. The spatial discretization method is the fifth-order Weighted Essen-
tially Non-Oscillatory scheme (Liu et al., 1994) for rain, and the first-order
upwind scheme for the motion vectors. The equirectangular projection is
used throughout the system, so that the input data are simply considered
as plain bitmap images, and the motion vectors are treated in the units of
pixels per hour, or 0.1° h⁻¹.
A TREC-based method is used to obtain motion vectors. This type of motion-tracking technique is also known as cross correlation or optical flow. The basic idea is to find a spatial shift of a local pattern (so-called “template”) between two or more consecutive time steps by computing spatial correlation under the assumption that the pattern shape does not change in time. Among all the possible location shifts, the one that gives the highest correlation is selected as the estimated motion. This procedure is called template matching, and the search space is called cross-correlation surface.

In this system, several changes are made to the original TREC: fractional motion, circular template, treatment of missing pixels, and quality control (Otsuka et al., 2016a,b).

To improve the accuracy of motion vectors for extrapolation, the system had seven major updates in its algorithms and parameters during the period from January 2016 to March 2018 (Table 1). These updates aim to improve the quality of motion vectors (V4, V10, V23), increase the number of available motion vectors (V4, V11, V23, V25), and stabilize the system (V1, V4a, V23, V25). The key points of each update are highlighted below:

- In the version described in Otsuka et al. (2016a), the advection sometimes showed numerical noise. To avoid that, V1 shortened the time interval of advection.
- V1 or earlier did not estimate motion vectors over weak precipitation.
areas. This degraded the performance over those areas due to the lack of information. V4 lowered the threshold of rainy pixel in TREC to compute motion vectors of weak precipitation.

- NRT initially assigns large negative values to missing pixels such as the land covered by snow (Seto et al., 2005). However, this caused numerical noise in advection mainly over winter Eurasia due to sudden changes of pixel values; this was not noticed by Otsuka et al. (2016a) because they investigated boreal summer only. V4a replaced the missing values by 0 mm h$^{-1}$ at the beginning of 12-hour forecast to suppress the noise.

- Raw TREC motion vectors tended to include erroneous values, leading to the lower forecast accuracy. V10 introduced two new algorithms to remove erroneous motion vectors. See Appendix B for details.

- V10 or earlier did not compute motion vectors near the south/north lateral boundaries to avoid incomplete coverage of TREC template and search area. However, the lack of information degraded the forecast accuracy near the boundaries. V11 computes motion vectors as long as they meet the quality control criteria.

- V11 or earlier tended to underestimate or miss motion vectors at high latitudes mostly due to the equirectangular projection. V23 intro-
duced latitude-dependent sizes of TREC template to solve this problem.

- In addition to the changes in V23, V25 introduced a latitude-dependent search space of TREC to improve this problem further.

Details of each update will be provided in Appendix B. Impacts of these updates will be presented in Section 3.

3. Results

First, Sections 3.1–3.2 describe overall performance of the system. Next, Section 3.3 provides quantitative comparisons between different versions at the timing of each update; this is mainly related to how motion vectors for extrapolation can be derived more accurately. Finally, Section 3.4 provides analyses on how an advection-diffusion equation can be stably constrained by data assimilation.

The accuracy of RNC precipitation forecast is verified against the GSMaP standard product (moving vector with Kalman filter, MVK) version 6 because MVK is supposed to be more reliable compared to NRT; MVK uses more satellite data, and considers deformation of rain areas and temporal change of rain rate in a better way (Ushio et al., 2009). The accuracy of tracking algorithm is additionally verified using NRT because the motion
vectors are designed to represent the motion of NRT precipitation pattern. The accuracy of RNC is compared with that of the NRT-based Eulerian persistence forecast (PER), which is considered as the baseline. Although the algorithm of NRT has been updated occasionally, both RNC and PER commonly includes the effects of those updates, so that the difference between RNC and PER is supposed to represent the effect of spatiotemporal extrapolation. This paper uses the operational version of RNC; creating a reanalysis data set with the latest algorithm is beyond the scope of this paper.

3.1 Visual analysis of spatial pattern

Figure 2 shows an example of nowcast initialized at 0000 UTC 23 March 2017 by the latest version (V25). The color shading represents hit (green), miss (red), and false alarm (blue) of rain rate greater than 0.1 mm h$^{-1}$ with respect to MVK. At the forecast time (FT) of 0 h, the initial condition is identical to NRT, i.e., most of the rainy pixels greater than 0.1 mm h$^{-1}$ are green in Fig. 2a; red and blue pixels also exist due to the differences between NRT and MVK. As FT increases, blue and red pixels increase. At FT = 12 h (Fig. 2g), red areas tend to appear to the east of blue areas at higher latitudes, indicating that the eastward motion of extratropical
cyclones tends to be underestimated; we will discuss this slow-bias issue later in the following sections.

Comparison between FT = 6 and 12 h indicates that rapid changes of the rain areas are one of the reasons for this underestimation of eastward motion (Figs. 2e,g); the rain area south of Australia quickly forms a new rain area to the east, and another T-bone rain area in the southern Pacific shows a quick shift to the southeast. These changes seem unpredictable in the linear sense.

3.2 Statistical verification

[Fig. 3 about here.]

Before investigating the temporal change of the forecast accuracy, the time-averaged performance is examined as a function of forecast time to provide basic information on the forecast skill. Figure 3 shows the mean threat scores (TS) against MVK for the threshold values of 0.1, 1, and 5 mm h\(^{-1}\) as a function of FT for RNC and PER, and RNC TS minus PER TS (\(\Delta\)TS), computed for the northern hemisphere (20\(^\circ\)–60\(^\circ\)N), the tropics (20\(^\circ\)S–20\(^\circ\)N), the southern hemisphere (20\(^\circ\)–60\(^\circ\)S), and the entire computational domain. In all the verification regions, TS is the highest with the threshold of 0.1 mm h\(^{-1}\) and lowest with 5 mm h\(^{-1}\). TS at FT = 0 h is smaller than unity, simply reflecting the difference between NRT and
MVK. Particularly, TS for 5 mm h\(^{-1}\) at FT = 0 h is less than 0.6, and at the 0.1 and 1 mm h\(^{-1}\) thresholds, TS are in the range 0.71 to 0.78, meaning that the differences between NRT and MVK precipitation are less noticeable for the lower rain thresholds.

The threat score difference \(\Delta\text{TS}\) is the largest for 0.1 mm h\(^{-1}\) and smallest for 5 mm h\(^{-1}\). Although TS is the highest over 20\(^\circ\)S–20\(^\circ\)N (Fig. 3b), \(\Delta\text{TS}\) is the smallest over 20\(^\circ\)S–20\(^\circ\)N, indicating that the linear extrapolation in the tropics is not as advantageous against PER as in the extratropics presumably due to slower motions of large-scale precipitation systems such as the Madden-Julian Oscillation. Note that the lifecycle of subgrid-scale convective cells does not affect the accuracy of space-time extrapolation on the spatiotemporal scale of 0.1\(^\circ\) × 0.1\(^\circ\) and one-hour even if convective systems play a dominant role in the tropics.

The analysis regions 20\(^\circ\)–60\(^\circ\)N and 20\(^\circ\)–60\(^\circ\)S show similar performances to each other (Figs. 3a,c). \(\Delta\text{TS}\) for 0.1 mm h\(^{-1}\) (red dashed) maximizes at FT = 5 h over 20\(^\circ\)–60\(^\circ\)N and 20\(^\circ\)–60\(^\circ\)S, whereas that over 20\(^\circ\)S–20\(^\circ\)N maximizes at FT = 3 h. These results indicate that the advantage of advection in weak rain areas lasts up to 12 hours, and it lasts longer in the extratropics than in the tropics. \(\Delta\text{TS}\) for 1 mm h\(^{-1}\) (green dashed) maximizes at FT = 3–4 h, and \(\Delta\text{TS}\) for 5 mm h\(^{-1}\) (blue dashed) always maximizes at FT = 1 h. The prediction skill for intense rain areas drops
quickly as FT increases. The general tendency is similar to the results in Fig. 5 of Otsuka et al. (2016a).

Next, the temporal change of the forecast skill in response to the system updates is examined. Figure 4 shows the time series of monthly-mean global TS and ∆TS. The performance of RNC for 0.1 mm h\(^{-1}\) improved during this period for all the forecast time, whereas that of PER did not show such a trend (Fig. 4a). The time series of ∆TS for 0.1 mm h\(^{-1}\) (Fig. 4d) has an annual cycle with two negative spikes around February and December 2016; details will be discussed in Fig. 6. The time series of ∆TS for 0.1 mm h\(^{-1}\) also indicates that the advantage of space-time extrapolation increases quickly between FT = 1 and 2 h.

The performance of RNC for 1 mm h\(^{-1}\) (Fig. 4b) is more stable than that for 0.1 mm h\(^{-1}\) during this experimental period. The difference between the nowcast and persistence (∆TS in Fig. 4e) shows a similar temporal change as in ∆TS for 0.1 mm h\(^{-1}\) (Fig. 4d), but the amplitude is much smaller. The advantage of nowcasting maximizes at about FT = 2–3 h for 1 mm h\(^{-1}\). This is consistent with the green dashed line in Fig. 3d. The performance of RNC for 5 mm h\(^{-1}\) is also stable during the experimental period (Fig.
4c), and the difference between RNC and PER for 5 mm h\(^{-1}\) is almost the same between FT = 1–3 h (Fig. 4f).

Although the scores for 1 and 5 mm h\(^{-1}\) imply that the changes in the system do not improve much the forecast performance, the threat scores computed with respect to NRT do improve during this experimental period (Fig. 5). Here, Fig. 5 shows the performance at FT = 1 h to highlight a time when advection is successful as a forecasting approach; longer forecasts are affected more strongly by the evolution of precipitation systems. Therefore, the changes in the system help better capture the motion of NRT precipitation. However, uncertainties in both NRT and MVK have a larger impact on the threat scores than the improvements in the motion vectors; improving the forecast performance requires improvements in the quality of input, too. As the precipitation rate increases, the discrepancy between NRT and MVK increases (Fig. 5c).

Figure 6 is similar to Figs. 4d–f, but verified in each region. ∆TS for 0.1 mm h\(^{-1}\) over 20°–60°S (Fig. 6g) shows the largest performance improvement among others; ∆TS increases by about 0.02–0.03 during this period. Another uniqueness in Fig. 6g is an increase of ∆TS with the forecast time. This may be related to faster “apparent” zonal motion of synoptic weather
systems in the units of pixels per hour over 40°–60°S on the equirectangular projection. A faster apparent motion is advantageous to the space-time extrapolation compared to the Eulerian persistence. In the northern hemisphere, in contrast, the north Pacific storm track region lies at slightly lower latitudes than the storm track region in the southern hemisphere (e.g., Catto et al., 2012), and this effect is weakened; an apparent zonal motion at 35°N on the equirectangular projection is 14% smaller than that at 45°S if the actual zonal motion is the same.

ΔTS for 0.1 mm h$^{-1}$ over 20°–60°N has large drops around February and December 2016 (Fig. 6a), whereas other regions or other thresholds do not show such a drop (Figs. 6b–i). This is caused by a numerical noise of advection along the boundaries between valid and missing pixels over Eurasia (Appendix B.3). The annual cycle of the performance drop appears because land with snow cover becomes missing pixels in GSMaP (Seto et al., 2005). The problem was solved by the update on 20 January 2017 (Appendix B.3); the boreal winter in 2017–18 did not show such a performance drop.

3.3 Impact of each system update

[Fig. 7 about here.]

Table 2

It is not realistic to rerun each version of the operational system for the entire period. Instead, it is a normal practice to run the old and new systems
in parallel, a.k.a. parallel run, at the time of each system update. This way,
we make sure that the new system runs properly in preparation to the actual
operational update in place. Figure 7 shows the threat score improvements
of RNC against MVK version 6 as a function of forecast time and latitude
due to the following system updates: V1 to V4 (Figs. 7a–c), V4a to V10
(Figs. 7d–f), V10 to V11 (Figs. 7g–i), V11 to V23 (Figs. 7j–l), and V23
to V25 (Figs. 7m–o). The verification periods are listed in Table 2. The
transition from V4 to V4a is not shown because of the misconfiguration of
covariance inflation (Appendix B.8). Note that impacts of each parameter
change or each new method on the forecast accuracy are assessed before
each system update, although differences between the major versions are
presented in this paper for simplicity.

[Fig. 8 about here.]

[Fig. 9 about here.]

a. V1 to V4

This update showed the largest improvement during January 2016–
March 2018 (Figs. 7a–c); the most significant improvements appeared at
40°S and 40°N at FT = 5 h for 0.1 mm h⁻¹. These changes are consistent
with the algorithmic update; computing additional motion vectors in the
weak rain areas expands the “observed” areas (Fig. 8a), leading to the highest improvement in the weak rain areas (Appendix B.2). Figure 9a shows that this update accelerates eastward motions in the extratropics and westward motions in the tropics. This was favorable for reducing the slow bias of the motions.

b. V4a to V10

In general, the performance at FT = 1–3 h improved at all latitudes; this is consistent with the update of motion vector quality control. Similar to the previous update, the forecasts improved the most in the extratropics around FT = 6 h for 0.1 and 1 mm h$^{-1}$ (Figs. 7d–f). In the tropics, TS improved up to FT = 3 h, but some degradation appeared at longer forecast time. This may be due to the nature of tropical convective systems; tracking an existing convective system precisely does not necessarily improve the longer forecasts beyond the life cycle of that convection. As a result of the stricter quality control, the number of available motion vectors decreased (Fig. 8b). Figure 9b indicates that the motion vectors that pass the quality control do not change the mean value before and after the update.

c. V10 to V11

TS slightly improved at the highest latitudes for 0.1 and 1 mm h$^{-1}$ (Figs. 7g,h). This is consistent with the increase of available motion vectors near
the lateral boundaries (Fig. 8c, Appendix B.5). The motion vectors that 
 existed before this update outside the boundary regions did not change by 
 this update (Fig. 9c). For 5 mm h\(^{-1}\), the TS difference is not always positive 
 around 60°S (Fig. 7i).

d. \(V11\) to \(V23\)

The forecasts improved the most in the extratropics at longer forecast 
 time (Figs. 7j–l); the number of available motion vectors also increased (Fig. 
 8d), and the eastward component of the motion vectors became stronger 
 (Fig. 9d). The accelerated eastward motions seemed to reduce the slow 
 bias. However, TS for 0.1 mm h\(^{-1}\) slightly degraded in the tropics, where 
 the number of available motion vectors decreased (Fig. 8d). Again, the 
 improvements are clearer for weaker precipitation rate. This is consistent 
 with the tuning of the spatial scale at high latitudes, and the performance 
 change in the tropics can be considered as a side effect due to the changes 
 in the quality control methods (Appendix B.6).

e. \(V23\) to \(V25\)

The forecasts improved the most between 40°–60°S, and the secondary 
 peak appeared around 30°–40°N; the eastward component of motion vectors 
 at these latitudes became stronger (Fig. 9e), reducing further the slow bias 
 of the extratropical cyclones (Fig. 2). These latitudes correspond to the
population of cold and warm fronts (e.g., Catto et al., 2012). This change is consistent with the introduction of latitude-dependent search space in TREC (Appendix B.7). The improvement is largest for 0.1 mm h$^{-1}$ and smallest for 5 mm h$^{-1}$. No difference appears in the tropics.

3.4 Analyses on the assimilation system

The ensemble Kalman filter finds an optimum solution based on the forecast ensemble covariance and observation error covariance. The observation error covariance is given a priori, whereas the forecast ensemble covariance is controlled by the internal dynamics and the covariance inflation method. In a numerical weather prediction (NWP) system, it is common that the internal dynamics plays the central role. However, the current system adopts an advection-diffusion equation; the internal dynamics lacks mechanisms of error growth that is essential in the real atmosphere. Therefore, the ensemble spread of motion vectors in the analysis cycle needs to be examined carefully.

First, an instantaneous distribution of the ensemble spread is examined to understand what uncertainties the advection-diffusion model represents. Figure 10 shows the horizontal distributions of rain, zonal component of analysis motion vectors $u^a$, ensemble spread of the zonal component of first
guess motion vectors, and corresponding analysis increments $\vec{u}^a - \vec{u}^f$ at 0000 UTC 25 December 2017.

An elongated area of large ensemble spread appears around $130^\circ$–$150^\circ$E, $20^\circ$–$30^\circ$N (Fig. 10c), which corresponds to a “frontal” region to the southeast of a rain area centered at $147^\circ$E, $40^\circ$N (Fig. 10a,b). This also coincides with a large increment in Fig. 10d; uncertainty in the location of shear line produces a large ensemble spread, and “observations” of motion vectors fix the location effectively based on the background error covariance structure. Note that this frontal structure does not necessarily correspond to the frontal system in the atmospheric dynamics; everything in the nowcasting system represents the apparent motion of rain patterns.

An area of large ensemble spread to the north of the rain area is produced by the covariance inflation method (Fig. 10c). In ordinary NWP systems, the forecast error grows following the internal dynamics, whereas the current extrapolation system lacks such internal dynamics and requires stronger covariance inflation. If not inflated artificially, the ensemble spread decreases continuously due to the dissipative nature of the advection-diffusion equation. If a new precipitation system appears in that high-spread area, motion vectors of the system will be assimilated quickly. More precisely, two consecutive images of a new precipitation system are needed to compute motion vectors of that precipitation system. A new precipitation system is usu-
ally small when it appears for the first time, and moves in the direction of
pre-existing motion vectors.

[Fig. 11 about here.]

As an operational system, the ensemble spread needs to stay within a
reasonable range; the assimilation system will blow up at some point if
the spread keeps increasing or decreasing. Figure 11 shows the time series
of ensemble spread of analysis motion vectors. The ensemble spread was
unstable in V1 (black), whereas the spread was mostly stabilized from V4
(red). The increase in the number of available motion vectors in V4 (Fig.
8a) seems to decrease the spread from V1 to V4. A small spread drop in
July 2016 seems to correspond to a bug fix in LETKF. Another drop in the
meridional component from December 2016 to February 2017 was caused by
the system misconfiguration. An increase of spread from V4a to V10 (green)
is consistent with the decrease of number of available motion vectors (Fig.
8b) due to the more strict quality control criteria in V10. A spread drop
from V10 to V11 (blue) is consistent with the increase in the number of
available motion vectors around the south/north lateral boundaries (Fig.
8c). From V11 to V23, the spread was slightly decreased. From V23 to
V25, the spread did not change much.
4. Discussion

The forecast error of space-time extrapolation comes from multiple sources: tracking error, advection error, and the error from the Lagrangian persistence assumption. The first two are the main themes of this paper, whereas the last one will be a future work beyond this paper. The system updates had clear contributions to the increased number of motion vectors (Fig. 8), the increased quality of motion vectors (Fig. 9), and the improved accuracy of forecast by advection (Fig. 7). The system strongly relies on the input data because the model consists of the advection and diffusion terms only; to constrain the behavior of the system, information needs to be extracted effectively from noisy observations.

As noted in Section 3, eastward motions of extratropical cyclones tend to be underestimated. This was partly caused by suboptimality of parameters such as the patch diameter and search space in TREC at high latitudes, and the problem was reduced by latitudinally-varying these parameters (Table 1, Figs. 7j–o and 9, Appendix B.6–B.7). There still remains the slow bias of motion vectors in the case of extratropical cyclones (Fig. 2); further improvements in both motion tracking and data assimilation are needed. Another issue in detecting motion vectors is spatiotemporal continuity of input data. For example, small red dots appear and disappear suddenly to the west of Australia in Figs. 2c,e,g. In this case, it is difficult to track the
motions of these areas. These sudden changes may occur due to the satellite-to-satellite differences of sensors used in GSMaP, as well as the algorithm to produce the mosaic product. In the present study, data assimilation provides reasonable estimates over these areas. In contrast, cloud tracking by geostationary meteorological satellites may be less influenced by the discontinuity of data.

In principle, spatiotemporal extrapolation cannot capture the lifecycle of extratropical cyclones. For example, a comma-shaped rain area in the northwestern Pacific (Fig. 2b) changes to a linear rain band (Fig. 2h) in 12 hours. NWP can predict the evolution of precipitation systems within the limit of predictability based on the physics, and machine learning techniques may also be able to predict the evolution based on the past data.

5. Summary

This paper described an overview of GSMaP RNC, a GSMaP-based global precipitation nowcasting system using data assimilation. The main foci were on 1) how to better estimate the motion vectors, and 2) how to stably constrain the advection-diffusion model with data assimilation.

The system has been stably running in real time since January 2016 for three and a half years as of July 2019, and seven major system updates were applied (Table 1). Most of the updates were related to better estimating
motion vectors. The forecasts have been disseminated via RIKEN’s and JAXA’s webpages every hour in real time under the weather forecasting license.

Verification against GSMaP MVK showed that the space-time extrapolation was working properly (Figs. 3–6). Comparison with the Eulerian persistence forecasts revealed that the advantage of space-time extrapolation has increased gradually during January 2016–March 2018 due to the seven major system updates (Figs. 4–6). Particularly, the updates ameliorated the winter performance drop in the northern hemisphere; the long-term operations revealed this seasonal performance drop and led to the improvement of the system. Comparisons of threat scores before and after each system update showed that the scores improved the most at around 40°S and 40°N (Fig. 7). Light precipitation areas improved significantly, whereas heavy precipitation areas did not improve as much.

Analyses on the ensemble spread showed that the increase and decrease of the number of available motion vectors changed the ensemble spread between each system update (Fig. 11). Motion vectors are effectively modified over the regions where the ensemble spread becomes larger, such as areas near the frontal systems (Fig. 10). Better quantifying the uncertainties of the motion vectors in the TREC estimations and in the first guess will be a good direction for improving further the stability of the system and the
forecast accuracy.

The space-time extrapolation method has an apparent limit of forecast accuracy particularly for strong rain areas (Fig. 3). It is natural to run an NWP system for longer forecasts beyond that limit; for example, Kotsuki et al. (2017) developed a global NWP system that assimilates GSMaP to better predict precipitation. In regional weather prediction, blending of extrapolation and NWP is widely used to take advantage of each of these systems (e.g., Golding, 1998; Sun et al., 2014). Blending is also beneficial in the global precipitation forecasting (Kotsuki et al., 2019).

Probabilistic forecasting seems to be an essential tool in practical precipitation nowcasting, and ensemble-based methods have been widely used (e.g., Germann and Zawadzki, 2004; Bowler et al., 2006). Our system uses an ensemble Kalman filter for the motion vector construction (Fig. 1), and the “observed” motion vectors are effectively assimilated using the background error covariance structure (Fig. 10). Although the current GSMaP RNC runs a deterministic precipitation forecast using the ensemble mean motion vectors, the system can be easily extended to an ensemble forecast.

Another direction of future improvements may be a use of data-driven approaches in nowcasting. One such approach is machine learning; for example, Han et al. (2017) used a support vector machine for precipitation nowcasting. As a quantitative precipitation estimation algorithm, Hirose
et al. (2019) adopted the random-forest algorithm. Another example is the analog forecasting (Lorenz, 1969); there are applications in precipitation nowcasting (e.g., Obled et al., 2002). These old but still potentially useful techniques with the aid of growing computer power and increasing data size will give us many possibilities of the precipitation nowcasting.

Acknowledgments

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Appendix
A. Weather forecasting license

A weather forecasting license is needed to issue weather forecasts by law in Japan. RIKEN obtained a permission from JMA in March 2017 (permission number 204), and the GSMaP RNC real-time products became open to public since May 2017. The licensed regions are the Japanese islands and the surrounding seas over $100^\circ$–$180^\circ$E, $0^\circ$–$60^\circ$N. Outside these regions, the Japanese law does not restrict issuing weather forecasts. Licensed forecasters need to examine the products prior to issuing the forecasts. The latest forecast for the Japanese islands and the surrounding seas is hidden on the product webpage to comply with the regulation until the forecasters decide to issue the forecast. Forecasting activities such as the forecast data and the issuer of each forecast need to be recorded for inspections by JMA.

B. Overview of the system updates

This section presents brief descriptions of each update. Some details will be described in Appendix C. The parameters below are manually tuned to maximize the forecast accuracy measured by the threat score.
B.1 Update on 1 January 2016 (V1)

- The time interval of advection $\Delta t$ was changed from 120 s to 60 s for numerical stability.

B.2 Updates on 15 March 2016 (V4)

- V1 suffered from lack of information over weak rain areas. Therefore, the definition of rainy pixel in TREC was changed from rain rate $R \geq 1 \times 10^{-3}$ mm h$^{-1}$ to $R \geq 0$ mm h$^{-1}$. This increases the number of available motion vectors by about four times (Fig. 8a).

- The quality control criterion of TREC motion vectors was changed. TREC estimates motion vectors by the template matching, where similarity is measured by the Pearson correlation coefficient $r$. The coefficient $r$ becomes much smaller than one if TREC fails to find a similar pattern. In this update, the criterion of acceptance was changed from $r > 0$ to $r > 1 \times 10^{-5}$. More strict quality control became possible because of the increased number of TREC motion vectors.
B.3 Update on 20 January 2017 (V4a)

• Missing pixels are initially assigned by large negative values in NRT. However, sudden changes of pixel values between valid rain rates and the missing values cause numerical noise in advection. To suppress the noise, the missing values in NRT are replaced by 0 mm h\(^{-1}\) at the beginning of 12-hour forecast.

B.4 Updates on 10 February 2017 (V10)

Although data assimilation reduces noise in the motion vector field, the quality of “observed” motion is still crucial. Thus, V10 introduced the following three changes.

• The quality control criterion of correlation coefficient in TREC was changed from \(r > 1 \times 10^{-5}\) to \(r > 0.2\).

• The quality of a motion vector does not solely depend on \(r\), but also clarity of the peak of \(r\) on a cross-correlation surface in TREC. To consider this effect, a criterion for the variable range of \(r\) (\(\Delta r\)) on a cross-correlation surface is introduced; motion vectors are accepted if \(\Delta r \geq 0.4\). See details in Appendix C.1.

• A new algorithm was introduced to remove artificial ring-shaped patterns that appeared frequently in the motion vector field due to the
use of finite template size in TREC. See details in Appendix C.2.

B.5 Update on 10 July 2017 (V11)

- Motion vectors near the south/north lateral boundaries were not computed in the previous versions to avoid incomplete coverage of TREC template and search area. However, this leads to lower performance near the boundaries. From this version, motion vectors are computed as long as they meet the quality control criteria.

B.6 Updates on 1 November 2017 (V23)

- The current system adopts the equirectangular projection for simplicity. However, this leads to suboptimality in globally-defined TREC parameters due to the differences in the length of the latitudinal circle and the typical spatial scales of tropical and extratropical weather systems. Therefore, the TREC template diameter $d_{CC}$ was changed from a fixed value of 46 pixels ($= 4.6^\circ$) to a function of latitude: 46 pixels for 20°S–20°N, 92 pixels for 30°–60°S and 30°–60°N, a quarter-wavelength sinusoidal function in between. This update accelerates the eastward component of motion vectors in the extratropics (Fig. 9d). The following three changes are made to introduce this latitude-dependent $d_{CC}$.
• The criterion for the variable range of $r$ in TREC was changed from
\[ \Delta r \geq 0.4 \] to a normalized version \[ \Delta r_N \geq 0.8 \] (Appendix C.1). The
quality control criterion of correlation coefficient was also changed to
\[ r > 0.6. \]

• Rain fields are smoothed only for the TREC computation by a box-
mean method with a box size of \(0.1d_{cc} \times 0.1d_{cc}\) (Appendix C.3).

• Minimum ratio of valid pixels within the template in TREC was
changed from 5% to 1.25%.

B.7 Updates on 1 March 2018 (V25)

• Although V23 improved the forecast accuracy at high latitudes, there
was still room for latitude-dependent optimization. Cross-correlation
was computed within a finite search space \(S\) defined by \(|(\delta i, \delta j)| \leq \)
\(L\), where \((\delta i, \delta j)\) represents the offset in the zonal and meridional
directions, and \(L = 0.6^\circ\). To take into account the length of latitudinal
circle, \(S\) is changed to \(|(\delta i \cos \theta, \delta j)| \leq L\), where \(\theta\) is the latitude of
analysis point. This accelerates the eastward component of motion
vectors at high latitudes (Fig. 9e), and slightly increases the number of
available motion vectors at high latitudes in the southern hemisphere
(indistinguishable in Fig. 8e).
• The time interval of advection $\Delta t$ was changed from 60 s to 30 s for numerical stability. This change is due to the introduction of latitude-dependent $S$ described above; the maximum zonal motion at high latitudes increases.

B.8 Other system changes

There are several other changes to the system. The computational performance was improved several times during this period. A bug fix of LETKF applied at 0100 UTC 5 July 2016 resulted in a jump in the time series of ensemble spread. MPI parallelization was introduced at 0400 UTC 16 October 2016. Another bug fix in LETKF was applied at 2200 UTC 6 December 2016. Covariance inflation for the north-south motion variable in LETKF was not applied unintentionally by mistake in the assimilation cycles from 1200 UTC 27 December 2016 to 2100 UTC 8 February 2017. This was caused by a system misconfiguration during the system update at 1200 UTC 27 December 2016.
C. Details of the system updates

C.1 Quality control of motion vectors using variable range of correlation coefficient

A cross-correlation method may fail to capture correct motions if the peak on a cross-correlation surface is not prominent. In some previous studies, for example, statistical significance of the peak was used to define the quality of motion vectors (Ikegawa and Horinouchi, 2016; Horinouchi et al., 2017). Here, a simple method is implemented to evaluate a distinct peak; the variable range of correlation coefficient $r$ on a cross-correlation surface, $\Delta r \equiv \max(r) - \min(r)$, is used as a proxy to the quality. From 10 February 2017, motion vectors are rejected if $\Delta r < 0.4$.

[Fig. C1 about here.]

Although this works well in general, this method sometimes rejects useful motion vectors; if a decorrelation length scale of a weather system around an analysis point $i$ is larger than a prescribed search space $S$ of TREC, $r$ does not drop to zero within $S$, resulting in $\Delta r \ll 1$ regardless of the estimation quality. See an example in Fig. C1; the random fields show a small $\Delta r$ (Figs. C1a,b), the sinusoidal functions with a short decorrelation length scale show a large $\Delta r$ (Figs. C1c,d), and the sinusoidal functions
with a long decorrelation length scale show a small $\Delta r$ within $S$ but $r \sim 1$ (Figs. C1e,f).

To avoid such a situation, $\Delta r$ is normalized by the “predicted” $\Delta r$ as follows:

$$
\Delta r_N(i, d_{CC}, S, t_{n-1}, t_n) \equiv \frac{\Delta r(i, d_{CC}, S, t_{n-1}, t_n)}{\Delta r(i, d_{CC}, S, t_{n-1}, t_{n-1})},
$$

(1)

where $d_{CC}$ is the diameter of the circular template for TREC, $t$ represents time, and the subscript $n$ denotes the time index. If $\min(r(i, d_{CC}, S, t_{n-1}, t_{n-1})) < 0$, $\Delta r$ is used instead of $\Delta r_N$. In the case of Fig. C1f, $\Delta r = 0.27$ and $\Delta r_N = 1.4$. From 29 November 2017, motion vectors with $\Delta r_N < 0.8$ are rejected.

C.2 Removing a ring-shaped noise in the motion vector computation

[Fig. C2 about here.]

Figure C2a shows an example of erroneous motion vectors; most of the motion vectors represent the motion of strong rain area moving to the right (shaded in red), whereas the edge of the motion vector field represents the motion of weak rain area moving to the left (blue). The discontinuity between the higher rain rate at the center and the surrounding lower rain rate makes this ring-shaped discontinuity in the motion vector field. This
pattern appears frequently in the real data due to noise in the rain field. To avoid this “ring effect,” the following procedure is introduced; if all the rainy pixels at time \( t - 1 \) with rain rate \( R \) greater than the threshold \( R_0 \) are located between the prescribed distances \( d_0/2 \) and \( d_{CC}/2 \) from the center of the template, the motion at that grid point is not computed. The diameter \( d_0 \) controls the ring effect, where \( d_0 \) ranges between 0 and \( d_{CC} \). By applying this method, the appearance frequency of this pattern decreases (Fig. C2b). From 10 February 2017, \( d_0 \) is set to 40 pixels with \( R_0 = 10^{-5} \) mm h\(^{-1} \).

C.3 Smoothing rain field in TREC

Since 29 November 2017, rain fields are spatially smoothed during the computation of cross-correlation. Raw rain fields include structures on the scales much smaller than the template size \( d_{CC} \). If the template size \( d_{CC} \) gets larger, it becomes more difficult to find the global maximum on a cross-correlation surface because of multiple local maxima that appear as a result of the scale gap. For example, small scale features may move differently from large scale features. Similarly, some portions of the template may move differently from other portions. To reduce this problem, rain fields are smoothed by two-dimensional box averaging; the box size is specified as \( 0.1d_{CC} \times 0.1d_{CC} \). This modification was introduced in association with the latitude-dependent template size.
References


Kotsuki, S., K. Kurosawa, S. Otsuka, K. Terasaki, and T. Miyoshi, 2019: Global precipitation forecasts by merging extrapolation-based nowcast...


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