SINGV-DA: A data assimilation system for convective-scale numerical weather prediction over Singapore

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Abstract

SINGV-DA is a convective-scale numerical weather prediction system with regional data assimilation for Singapore and the surrounding region. This article documents SINGV-DA’s current operational configuration and the sensitivity studies that influenced its development. We show that background error covariances derived by bootstrapping (via the lagged National Meteorological Centre method) contain spurious vertical structures at higher model levels that may degrade forecast performance. We found that SINGV-DA precipitation forecasts are sensitive to horizontal resolution and lateral boundary conditions. Our observing system experiments reveal that satellite radiance assimilation, while clearly beneficial for precipitation forecasts in this region, adversely affected model background temperatures and winds at higher altitudes. Benchmarked against the forecast model in isolation, the regional DA system adds significant value to precipitation forecasts in the nowcasting range, but not at longer lead times. Our findings point to the need for further research and development to improve the system.

KEYWORDS

background error covariances, convective-scale, data assimilation, numerical weather prediction, observations, Singapore

1 INTRODUCTION

Singapore is a small island state in the western Maritime Continent separated from the larger land masses of Sumatra and Peninsular Malaysia by narrow sea straits (Figure 1). Convective processes driven by solar heating play a dominant role in the weather systems of this region. In the absence of strong synoptic forcing, these processes often lead to localised heavy precipitation over land associated with deep convection. Forecasting these localised thunderstorms remains a challenge for national hydrological and meteorological services in the region.
To improve weather forecasts in this region, Meteorological Service Singapore (MSS), in collaboration with the UK Met Office, has developed a tropical version of the Met Office’s UKV (Tang et al., 2013) for Singapore, named SINGV (Huang et al., 2019). This is a first-of-its-kind convection-permitting numerical weather prediction (NWP) system for the deep Tropics in operations.

The initial conditions for SINGV can be taken from analyses produced by a global or a regional data assimilation (DA) system. With initial conditions based on global analyses, and with lateral boundaries forced by the global model, SINGV functions as a dynamic downscaler of global model forecasts (hereafter SINGV-DS). The change in model physics and resolution produces spin-up effects that result in poor short-range forecasts from SINGV-DS. A regional DA system that is coupled to SINGV (hereafter SINGV-DA) significantly reduces the impact of spin-up on model performance.

On the other hand, regional DA tends to produce analyses that are deficient in large-scale information. The data assimilation problem is compounded by the paucity of in situ observations over the Maritime Continent and the absence of quasi-geostrophic balance between mass and wind field increments in the Tropics (Žagar et al., 2004).

There are additional challenges associated with convective-scale DA that operational centres around the world have begun to tackle (Gustafsson et al., 2018). Traditional techniques developed for synoptic-scale DA may be ineffective at convective scales where nonlinear dynamics dominate and forecast errors deviate significantly from Gaussianity (Chen and Snyder, 2007). Also, unbalanced flows triggered by convection and cloud processes violate the balance assumptions generally applied to constrain background error covariances (Vetra-Carvalho et al., 2012). The use of high-density observations in convective-scale DA is hampered by inadequate specifications of observation-error correlations (Rainwater et al., 2015).

This article adds to the scientific literature on convective-scale DA by detailing some of the challenges and findings connected with the development of SINGV-DA. The organisation of the rest of this article is as follows. Section 2 gives an overview of the SINGV-DA system. Section 3 documents some of the sensitivity studies that influenced the development of the system. In Section 4, we consider the value that the regional DA system adds to SINGV as a downscaler of global forecasts. We conclude with a summary of our key findings and some pointers for future research and development.

2 | THE SINGV-DA SYSTEM

In many respects, the SINGV-DA system, which went into operations on 1 July 2019, is similar to that of the Met Office’s regional NWP system for the United Kingdom (UKV) prior to July 2017, as described in Section 2.3 of Gustafsson et al. (2018). SINGV-DA uses an incremental three-dimensional variational (3D-Var) approach with FGAT (first guess at appropriate time) and runs...
### TABLE 1 Overview of SINGV-DA

| Forecast model | Horizontal resolution: 0.0135° (approximately 1.5 km) |
|----------------|-------------------------------------------------------|
|                | No. of grid points: 1,092 × 1,026                      |
|                | No. of vertical levels: 80                             |
|                | Model top: 38.5 km                                      |
| DA method      | Incremental 3D-Var with FGAT                           |
| Control variables | Stream function, velocity potential, unbalanced pressure, transformed humidity |
| Control variable transform | $U = U_p U_v U_h$                                         |
|                | $U_p$: Parameter transform                             |
|                | $U_v$: Vertical transform                              |
|                | $U_h$: Horizontal transform                            |
| Estimation of background error covariances | Lagged NMC method                                       |
| Initialisation | Incremental analysis update (IAU) from $T - 1$ to $T + 1$ |
| DA cycle       | 3-hourly                                               |
| Lateral boundary conditions | ECMWF (3–12 hr lag)                                     |
| Soil moisture and sea-surface temperature | UK Met Office global model analyses, updated daily in SINGV-DA at the 0900 UTC cycle |
| Observation cut-off | 180 min                                               |
| Observation bias correction | Variational bias correction for satellite radiances (Cameron and Bell, 2015) |

on a three-hourly cycle. The control variables are stream function, velocity potential, unbalanced pressure, and a transformed humidity (Ingleby et al., 2013). In the spatial transform, the error covariances are first projected onto vertical modes. The horizontal transform to spectral space is then applied to each of these vertical modes (Bannister, 2008b).

The background error covariances for SINGV-DA were estimated using the lagged NMC method (Široká et al., 2003), which is a modification of the National Meteorological Centre (NMC) method (Parrish and Derber, 1992) for limited area models (LAMs). The $B$-matrix approximation in the current operational set-up was derived by differencing $T + 12$ and $T + 6$ forecasts from an early standalone version of the forecast model over the training period 22 January to 6 March 2013. The impact of background error covariances on system performance is detailed in Section 3.1. An overview of the SINGV-DA system is given in Table 1.

SINGV-DA currently assimilates conventional surface and upper-air observations, satellite radiances from a number of instruments, and satellite-derived wind and cloud observations. Table 2 lists the observations assimilated in the system and their availability at each cycle over a typical day. SINGV-DA is also capable of assimilating radar radial velocity data and radar-based precipitation rate analyses, although this is currently at the experimental stage pending better quality control of radar data.

### 3 | SENSITIVITY STUDIES

The development of the SINGV forecast model and the DA system spanned 5 years, during which numerous configurations were tested and evaluated. The results of several sensitivity studies with SINGV-DA are documented in this section to inform future developments in convective-scale DA, particularly for the Tropics.

To evaluate impacts on model performance, we looked at:

1. First-guess departures (Observation Minus Background, OMB) for various meteorological parameters;
2. Mean errors and root-mean-square errors (RMSEs) of model forecasts relative to rawinsonde observations; and
3. Fractions skill scores (FSS) for precipitation forecasts (Roberts and Lean, 2007) verified against the Global Precipitation Measurement (GPM) Integrated
TABLE 2  Data availability per cycle in the SINGV-DA system

| Observations | Cycle (UTC) |
|--------------|-------------|
|              | 0000 | 0300 | 0600 | 0900 | 1200 | 1500 | 1800 | 2100 |
| Surface      |       |       |       |       |       |       |       |       |
| Aircraft     |       |       |       |       |       |       |       |       |
| Sonde        |       |       |       |       |       |       |       |       |
| CrIS         |       |       |       |       |       |       |       |       |
| IASI         |       |       |       |       |       |       |       |       |
| AIRS         |       |       |       |       |       |       |       |       |
| AHIASR       |       |       |       |       |       |       |       |       |
| AHIICLR      |       |       |       |       |       |       |       |       |
| MT-SAPHIR    | Variable: Two to five times a day |
| ATMS         |       |       |       |       |       |       |       |       |
| MHS          |       |       |       |       |       |       |       |       |
| GeoCloud     |       |       |       |       |       |       |       |       |
| Satwind      |       |       |       |       |       |       |       |       |
| Scatwind     |       |       |       |       |       |       |       |       |

Note: Sonde data includes both TEMP (at 0000 and 1200 UTC) and PILOT (at 0000, 0600, 1200 and 1800 UTC) reports. The treatment of advance Himawari imager all-sky radiances (AHIASR) follows the approach proposed by Pavelin et al. (2008), and only radiances above low cloud are assimilated in the current configuration. GeoCloud refers to pseudo-observations of cloud at the cloud top (Renshaw and Francis, 2011) derived from AHI imagery. Satwind refers to AHI-derived atmospheric motion vectors, whereas Scatwind refers to sea-surface winds derived from Advanced Scatterometer (ASCAT).

FIGURE 2  SINGV forecast model versions. Each version represents one year of development work in the five-year project (May 2013–April 2018)

Multi-satellite Retrievals for GPM (IMERG) data product (Hou et al., 2014) over the model domain.

While the DA system is the focus of this section, its performance cannot be decoupled from that of the forecast model. The development of the forecast model has been detailed in a separate article (Dipankar et al., 2020); an overview is shown in Figure 2. Reference will be made to the model versions in the following sections.

3.1 Impact of background error covariances

The lagged NMC method was used to estimate the background error covariances for SINGV-DA. An early standalone version of the forecast model at 4.5 km horizontal resolution was used to generate an initial approximation of the B-matrix for SINGV-DA. This baseline approximation was based on differences between pairs of T + 12 and T + 6 forecasts (four per day) over the training period 22 January to 6 March 2013.

Intuitively, the B-matrix model can be improved by using training data produced by a forecast system with a regional DA component (i.e. bootstrapping with an older B-matrix model), reducing the forecast length difference to match the three-hourly analysis updates, and updating the forecast model version. Accordingly, we generated new training data spanning 16 August to 13 October 2016 using SINGV-DA with the baseline covariances and later versions of SINGV (at 4.5 km horizontal resolution), using the differences between T + 6 and T + 3 forecasts as estimates of forecast error.

Figure 3a shows the vertical auto- and cross-correlations of the control variables based on the initial set of training data (without regional DA). The strong anti-correlation between levels 0–40 (0–8 km) and levels 40–60 (8–19 km) in the velocity potential (CHI) autocorrelation is particularly prominent in this plot. In the subsequent training data produced by SINGV-DA, the
anti-correlation between levels 0–15 (up to 1.5 km) and levels 40–60 is substantially weaker. An example with version 3.1 of the forecast model is shown in Figure 3b, but the same observation holds true with other versions of SINGV. Thus it appears that the inclusion of regional DA resulted in fundamental changes in the covariance structures, whereas forecast model upgrades produced comparatively modest differences.

This is also evident in the horizontal length-scales associated with the vertical modes of the control variables. As Figure 4 shows, the length-scale changes associated with model upgrades are relatively small compared to those due to bootstrapping. The general reduction in horizontal length-scales is consistent with the shorter forecast length difference in the second-generation training data compared to the baseline.

We also studied the impact of changing the control variable transform order. In the original transform order, hereafter referred to as the empirical vertical mode (EVM) covariance formulation, the vertical transform from model levels to empirical vertical modes is performed before the horizontal transform from grid-point space to spectral space. Reversing the transform order gives us a vertical transform that is a function of horizontal wave number (Wlasak and Cullen, 2014). This model level (ML) covariance formulation preserves the spectral characteristics of the training data and allows additional small-scale structure to be assimilated.

The effect of spatial transform order on analysis increments was observed mainly in the winds. Compared to the EVM formulation, the ML covariance formulation produced wind increments that are much more localised (Figure 5). The ML formulation also improved innovation statistics across many satellite channels. This is illustrated in Figure 6 with the CrIS (Cross-track Infrared Sounder) mean bias (OMB) statistics. Thus it appears that the ML covariance formulation is a better alternative to the EVM approach.

Contrary to expectations, the combination of more up-to-date error statistics derived by bootstrapping and a better spatial transform order did not translate into improvements in forecast performance. Compared to the baseline covariance model, the new model produced generally larger biases and RMSEs in forecasts of upper-air temperature and relative humidity (Figure 7). The consequent impact on precipitation forecasts was clearly negative (Figure 8). These findings were corroborated by later trials with the 1.5 km forecast model.

The degradation in forecast performance may be due to stratospheric ringing in the analysis increments resulting from spurious oscillatory structures in the vertical correlations over model levels in the stratosphere. Careful examination of the vertical correlations (Figure 3), particularly for velocity potential, show that these structures are present in both sets of training data, but they are clearly amplified in the second-generation training data.
This is a flaw of the NMC method that appears to be exacerbated by bootstrapping (Jackson et al., 2008). There are plans at the Met Office to deal with this issue. The interim solution for SINGV-DA is to use the baseline background error covariances derived by downscaling global forecasts.

### 3.2 Impact of model resolution

The horizontal resolution of the forecast model in a convective-scale DA system is an important determinant of system performance inasmuch as convective processes are better resolved as the resolution increases (Lean et al., 2008). The development of SINGV-DA was largely carried out with the forecast model resolution fixed at 4.5 km and the increment resolution at 4.25 km. A higher resolution (1.5 km forecast model; 2.85 km increment resolution) was specified, however, for the final operational configuration. This necessitated reducing the forecast model time step; all other aspects of the system (physics parametrizations, observation thinning, etc.) were unchanged.

We evaluated the performance of both configurations based on precipitation FSS and other metrics. To calculate FSS, precipitation forecasts from both configurations were re-gridded to the resolution of the observation dataset (GPM IMERG), that is, 0.1°.

Hinton diagrams of the performance of a suite with a 4.5 km forecast model relative to an equivalent suite employing a 1.5 km model are shown in Figure 9. They clearly show that the 1.5 km configuration gave better rainfall forecasts than the equivalent 4.5 km system at all forecast lead times for all but the highest absolute rainfall thresholds. The higher-resolution configuration also gave better forecasts of temperature, relative humidity and winds at the surface (not shown).

### 3.3 Impact of lateral boundary conditions

SINGV was originally designed to be driven by the Met Office’s operational global model through its lateral
boundaries. An option was later added to allow SINGV to be driven by the European Centre for Medium-range Weather Forecasts (ECMWF) global model. The impact of the driving model on SINGV’s rainfall forecasts proved to be significant.

The performance of a suite driven by the Met Office global model relative to one driven by the ECMWF model is shown in Figure 10. The latter gave better rainfall forecasts than the former across all but the highest absolute rainfall thresholds, and the differences increased with forecast range as the influence of initial conditions decayed.

The improvement in rainfall forecasts with ECMWF lateral boundary conditions (LBCs) may be attributed to more accurate wind forecasts over the Tropics at both 850 and 250 hPa in the ECMWF global model compared to the Met Office’s model (Haiden et al., 2019).

3.4 Impact of observations

The performance of an NWP system is undeniably tied to the number and quality of the observations assimilated into the system. The question is, which observation types have the largest impact? To examine the impact of observations on SINGV-DA, which is perhaps the only operational NWP system with regional DA that straddles the Equator, a set of observing system experiments (OSEs) were performed over a 12-day period in October 2018. The experimental period covered the passage of an enhanced convective phase of the Madden–Julian Oscillation across the Indian Ocean bringing widespread rainfall to the western Maritime Continent.

The set of experiments comprised a control run that made use of all available observation types and six separate data-denial experiments, each excluding a different observation type (aircraft, sonde, satellite radiances, atmospheric motion vectors, scatterometer winds, and surface observations). Figure 11 gives a sense of the number and coverage of the different observations assimilated into the control experiment at various cycles on 3 October 2018.

Each experiment was initialised at the 0000 UTC cycle on 1 October 2018 with the global ECMWF analysis and cycled at three-hourly intervals to the 2100 UTC cycle on 12 October. To minimise the influence of the cold start, we...
excluded the DA statistics and model output from 1 and 2 October from further analysis and evaluation.

The change in RMS values of rawinsonde OMB for relative humidity, temperature and wind due to the exclusion of the above-mentioned observation types from SINGV-DA is shown in Figure 12. Positive values signify that the RMSEs increased relative to the control run when the observations were excluded, indicating a degradation of the model background. The impact of each observation type on model background accuracy is proportional to the magnitude of the resultant change in RMSEs. The 95% confidence intervals show how variable the impacts were from one cycle to another.

The plots in Figure 12 indicate that, in general, the impact of any one group of observations on background errors is quite small, relative to the variability between cycles and between model levels. This suggests that the effect of data loss due to the omission of any observing system is mitigated by the availability of other observations with overlapping influence in space and time. Thus the SINGV-DA system appears to be robust to data outages.

Notwithstanding the general statement above, there were significant changes in RMSEs at certain levels for each of the observed parameter. The assimilation of surface observations reduced background errors in near-surface relative humidity and temperature, as
Figure 8 Fractions skill scores at a spatial scale of 19 grid lengths (1.9°) for forecasts of 3 hr precipitation (≥10 mm) over the SINGV domain for October 2016 from the control (using the baseline covariance model) and experimental (using a bootstrapped covariance model with a swapped spatial transform order) configurations. SINGV version 4.1 was used in both configurations expected, while rawinsonde observations and atmospheric motion vectors had a positive (albeit small) impact on background wind errors over many of the mid- to upper levels.

Satellite radiances, more than any other group of observations, had a clear impact on relative humidity and temperature errors at the higher model levels. Oddly, the impact of assimilating satellite radiances was positive for relative humidity but negative for temperature. The assimilation of satellite radiances was also slightly detrimental for wind at most levels above 35. On the other hand, the assimilation of satellite radiances did reduce temperature errors over much of the lower troposphere.

The impact of the various observation types on precipitation forecasts is shown in Figure 13. The assimilation of satellite radiances had the largest positive impact on precipitation forecasts, diminishing with increasing rain intensity and forecast range. Atmospheric motion vectors also contributed to forecast accuracy, particularly at the higher rainfall thresholds. The benefit of assimilating scatterometer winds is noteworthy, given that the data are available only once daily (Table 2), highlighting the important role that low-level convergence plays in thunderstorm initiation in this region (Weller et al., 2017).

Among the conventional observations, surface observations had the largest impact on precipitation forecasts. This suggests that information on low-level conditions and/or cloud coverage is important for accurate rainfall forecasts. The value of surface observations is possibly amplified by the relatively good temporal (Table 2) and spatial (Figure 11) coverage compared to rawinsonde and aircraft observations.

4 BENCHMARKING SINGV-DA AGAINST SINGV-DS

The development of SINGV-DA was carried out concurrently with the development of SINGV as a downscaler. By comparing SINGV-DA forecasts with those produced by SINGV-DS, we were able to identify potential problems

Figure 9 Hinton diagrams of the performance of a 4.5 km suite over the model domain relative to a 1.5 km suite, at a spatial scale of 5 grid lengths (0.5°), for various 3 hr rainfall thresholds and at increasing forecast lead times, averaged over all cycles in (a) August and (b) October 2017. Downward pointing triangles indicate that the 1.5 km suite gave better precipitation forecasts on average than the 4.5 km suite, with the magnitude of the difference (normalised by the maximum absolute difference indicated at the top of each matrix) indicated by the size of the triangle. A black outline denotes that the difference is statistically significant at the 5% level based on the Wilcoxon signed-rank test.
with the DA system. Benchmarking SINGV-DA against SINGV-DS also allowed for the value added by regional DA to be assessed. It would not be expedient to maintain and run a regional DA system unless it added value to the forecasts of a computationally cheaper and easier-to-maintain downscaler.

We carried out experimental runs with SINGV-DA and SINGV-DS, both using the latest forecast model version (SINGV 5.0), covering the period 1–30 April 2018. Climatologically, April falls in the Singapore inter-monsoon period and is characterised by strong insolation and light winds, giving rise to predominantly convective and localised thunderstorms (National Environment Agency, 2009).

While SINGV-DS takes its initial conditions as well as lateral boundary conditions (LBCs) from the global driving model (ECMWF), SINGV-DA is initialised independently of the driving model. Thus each SINGV-DA cycle may begin as soon as observations for that cycle arrive. In the operational set-up, to improve the timeliness of model forecasts, we run the 0000 and 1200 UTC cycles of SINGV-DA ahead of receiving ECMWF model output for those cycles, which means that the LBCs for the 0000 and 1200 UTC cycles have to be taken from the preceding ECMWF cycle. The LBCs are then updated at the 0300 UTC cycles.

**Figure 10** Similar to Figure 9, except this shows the performance of a Unified Model (UM)-driven suite over the model domain relative to an ECMWF-driven one averaged over all cycles in November 2016.

**Figure 11** Data coverage plots showing (a) the conventional observations assimilated in the 0000 UTC cycle, (b) the satellite radiance observations assimilated in the 0600 UTC cycle (upper right), and (c) satellite retrievals of atmospheric motion vectors and sea-surface winds in the 1500 UTC cycle (bottom) on 3 October 2018.
FIGURE 12  Change in RMS values of rawinsonde OMB for relative humidity (%), temperature (K) and wind (m s$^{-1}$) for each OSE relative to the control run, averaged over all cycles in the evaluation period (3–12 October 2018). The observation processing system calculates OMBs at model levels, after averaging observations within model layers. The error bars show the 95% confidence intervals for the mean differences.
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FIGURE 13 Similar to Figure 9, except these show the difference in performance over the model domain (area 539) between each OSE and the control run, averaged over all cycles between 3 and 12 October 2018.

and 1500 UTC cycles. We used the same set-up for the experiments, as summarised in Table 3.

For comparisons between SINGV-DA and SINGV-DS, the 0300 and 1500 UTC cycles of the former are paired with the 0000 and 1200 UTC runs respectively of the latter, since these pairs have common LBCs and are completed at roughly the same times in the operational schedule. For each model forecast run, the FSS are calculated over the model domain for various rainfall thresholds and spatial scales at increasing lead times. The differences in FSS between each pair of model forecasts are then calculated. Finally, the mean differences of the 60 pairs of model forecasts are calculated and the statistical significance assessed using the Wilcoxon signed-rank test.

Figure 14 shows the results of the above procedure for a spatial scale of five grid lengths. There are considerable and statistically significant differences in skill between SINGV-DA and SINGV-DS up to T + 12 (with respect to the SINGV-DA forecast reference times). The influence of the LBCs relative to that of the initial conditions increases with forecast range so there is little difference in skill between the forecasts produced by SINGV-DA and SINGV-DS beyond T + 12.

The first 3 hours’ rainfall forecast produced by SINGV-DA is typically much better than the corresponding forecast from SINGV-DS. This is testament to one of the benefits of a full-cycling DA system, namely, it requires very little spin-up time compared to a downscaler. On the other hand, given the 3 hr cut-off time for observations, the first 3 hours’ forecast is of no operational value.

Once SINGV-DS has achieved proper spin-up, which is 6 to 9 hr after model initialisation, its rainfall forecasts tend to be better than SINGV-DA’s. Thus, beyond T + 3, the SINGV-DA added value diminishes and is mostly negative, falling to its lowest between T + 9 and T + 12. This indicates perhaps that the regional analyses are deficient in some respects relative to the global analyses used to initialise SINGV-DS.

Similar findings have been reported by Sun et al. (2012) and Wang et al. (2014): model forecasts initialised...
with regional analyses tend to be worse than those initialised with global analyses after spin-up. On the other hand, Gustafsson et al. (2018) showed that, by using more sophisticated DA methods and/or assimilating additional local observations, convective-scale DA can significantly improve precipitation forecasts up to T + 12 or beyond.

Although the results presented in this section indicate that the regional DA system does not add value to the forecasts that can be derived by simply downscaling global model output, we have not taken into account the benefits that may be derived from the intermediate SINGV-DA cycles between 0300 and 1500 UTC. One obvious benefit stems from the fact that SINGV-DA is updated more frequently than SINGV-DS: the three-hourly update cycles give forecasters a means of tracking weather developments more frequently through the day than is possible with the 12-hourly downscaler runs.

5 CONCLUSIONS

The development and implementation of a DA system for operational NWP is a major undertaking. Ignoring aspects related to the forecast model (resolution, LBCs, etc.), the performance of a DA system is a function of (at least) the assimilation method adopted, the calibration (i.e. error statistics), and the observations assimilated. The time frame of the SINGV project did not allow for the fine-tuning of all components of the DA system but, as this article shows, many aspects were covered in the development and evaluation programme leading to an operational convective-scale DA system for Singapore.

Compared to the convective-scale DA and forecasting systems at other operational centres (Gustafsson et al., 2018), SINGV-DA is not ground-breaking in the methods used nor in the observations assimilated, but it does represent an important step forward in its application to the meteorologically complex Maritime Continent region. In this concluding section, we summarise the findings from our sensitivity studies and suggest areas for further research and development.

5.1 Key findings

Our investigations highlight the importance of the background error covariance model in a DA system. There is evidence that the ML covariance formulation is a better approach to model the covariances than the EVM method. However, among all the covariance models evaluated, the baseline covariance model produced the best overall outcome in terms of forecast performance, even though it was
derived by downscaling global forecasts with an old version of the forecast model and formulated using the EVM approach. The issue appears to be related to the training data; the bootstrapping process significantly altered vertical correlation structures and amplified oscillations in the correlations over model levels in the stratosphere.

The impact of horizontal resolution is clear. Dramatic improvements in SINGV-DA forecast performance were obtained by simply increasing the horizontal resolution of the forecast model and the analysis, without any changes to observation processing.

While accurate initial conditions – the main concern in DA – are important, the influence of LBCs becomes dominant within a few hours (Gustafsson et al., 2018). The impact of LBCs was detected in SINGV-DA precipitation forecasts within the first 3 hr of forecast runs and increased with forecast range. Clearly, the driving model is an important consideration for operational centres running LAMs to produce high-resolution forecasts.

Previous studies with global models (e.g. Bouttier and Kelly, 2001; Lorenc and Marriott, 2014) have shown that the assimilation of satellite radiances substantially improves model forecasts. We found, however, that assimilating satellite radiances increased SINGV-DA background RMSEs with respect to rawinsonde observations of temperature and wind at upper-tropospheric and stratospheric levels. These adverse effects may be an indication of problems with the radiative transfer models and/or bias correction coefficients at high altitudes. On the other hand, the exclusion of satellite radiances, more than any other type of observation, had an unambiguous negative impact on SINGV-DA precipitation forecasts up to at least T + 12.

The OSEs also show that the impact of any observing system on an NWP system is a function of its uniqueness with respect to other observing systems. Observing systems with overlapping coverage in space and time, such as rawinsonde observations, atmospheric motion vectors and satellite radiances, mitigate each other’s impact on model performance, whereas observing systems that cover a less-redundant observation space, such as surface observations and scatterometer winds, exert a disproportionate influence.

5.2 Areas for further research and development

The work described in this article represents only the beginning for SINGV-DA as an operational NWP system. There is certainly scope for further research and development to improve its performance.

In the first place, a better background error covariance model is needed. It appears to us that the properties of this model are fundamentally a function of the calibration method, the training data and, to a lesser degree, the model formulation. With regard to the calibration method, we see a need to suppress the spurious correlations introduced by the NMC method (and amplified by bootstrapping), or adopt an alternative approach (Bannister, 2008a; Jackson et al., 2008; Brousseau et al., 2011). Up-to-date training data produced by the latest version of the model would also be necessary for more-accurate error statistics. Finally, there may be a need to revisit the issue of spatial transform order with the new error statistics.

Secondly, based on the OSE results presented in this article, there is warrant for a more in-depth study of the impact of satellite radiance assimilation on the performance of SINGV-DA. The study period should be extended to verify the preliminary findings in this article. Separate OSEs – each excluding a different satellite instrument – may help in identifying the instrument(s) causing detriment to model forecasts at upper tropospheric and stratospheric levels.

Thirdly, additional sources of high-resolution observations should be investigated. Weather radar data (reflectivities and radial winds) have proven to be valuable and are already being assimilated in many operational convective-scale NWP systems (e.g. Brousseau et al., 2014; Benjamin et al., 2016). The impact for SINGV-DA, however, may not be significant, given that MSS can only access Singapore’s radar data, which cover a small part of the model domain. Mode-S Enhanced Surveillance (EHS) radars are another potentially useful source of high-resolution upper-air observations for SINGV-DA (Strajnar, 2012; Gustafsson et al., 2018).

Last but not least, there is potentially much to be gained by using a more sophisticated DA method. As Section 4 shows, over the operationally useful forecast range, SINGV-DA forecasts are no more skilful than those produced by SINGV-DS. In some respects, this is not surprising. In the first place, while a regional analysis may contain small-scale information absent in a global analysis, the former is necessarily deficient in large-scale information as a consequence of the limited area domain. We would also expect global analyses from ECMWF to be generally better than SINGV-DA analyses by virtue of the implicit use of flow-dependent structure functions through 4D-Var, which is further constrained by the background errors from an ensemble of data assimilations.

These differences between the global and regional analyses point to a two-pronged approach to improving SINGV-DA analyses. First, we could supplement the small-scale information in the regional analysis with...
large-scale information from the global analysis by blending the two using a spatial filter (e.g. Wang et al., 2014). To introduce flow-dependent “errors of the day” into the regional analysis increments, we could adopt a more advanced DA method such as 4D-Var or a hybrid ensemble-variational approach.

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**REFERENCES**

Bannister, R.N. (2008a) A review of forecast error covariance statistics in atmospheric variational data assimilation. I: Characteristics and measurements of forecast error covariances. *Quarterly Journal of the Royal Meteorological Society*, 134, 1951–1970.

Bannister, R.N. (2008b) A review of forecast error covariance statistics in atmospheric variational data assimilation. II: Modelling the forecast error covariance statistics. *Quarterly Journal of the Royal Meteorological Society*, 134, 1971–1996.

Benjamin, S.G., Weygandt, S.S., Brown, J.M., Hu, M., Alexander, C.R., Smirnova, T.G., Olson, J.B., James, E.P., Dowell, D.C., Grell, G.A., Lin, H., Peckham, S.E., Smith, T.L., Moninger, W.R., Kenyon, J.S. and Manikin, G.S. (2016) A North American hourly assimilation and model forecast cycle: the rapid refresh. *Monthly Weather Review*, 144, 1669–1694.

Bouttill, F. and Kelly, G. (2001) Observing-system experiments in the ECMWF 4D-Var data assimilation system. *Quarterly Journal of the Royal Meteorological Society*, 127, 1469–1488.

Brousseau, P., Berre, L., Bouttill, F. and Desroziers, G. (2011) Background-error covariances for a convective-scale data-assimilation system: AROME-France 3D-Var. *Quarterly Journal of the Royal Meteorological Society*, 137(655), 409–422.

Brousseau, P., Desroziers, G., Bouttill, F. and Chapnik, B. (2014) *A posteriori* diagnostics of the impact of observations on the AROME-France convective-scale data assimilation system. *Quarterly Journal of the Royal Meteorological Society*, 140(680), 982–994.

Cameron, J. and Bell, W. (2015) Pre-operational testing of Variational Bias Correction (VarBC). *Satellite Applications Technical Memorandum* 37. Exeter, UK: Met Office.

Chen, Y. and Snyder, C. (2007) Assimilating vortex position with an ensemble Kalman filter. *Monthly Weather Review*, 135, 1828–1845.

Dipankar, A., Webster, S., Furtado, K., Wilkinson, J., Sanchez, C., Lock, A., North, R., Sun, X., Vosper, S., Huang, X.-Y. and Barker, D. (2020) SINGV: a convective-scale weather-forecast model for Singapore, in preparation.

Gustafsson, N., Janjić, T., Schraff, C., Leuenberger, D., Weissmann, M., Reich, H., Brousseau, P., Montmerle, T., Wattrelot, E., Bučánek, A., Mile, M., Hamdi, R., Lindskog, M., Barkmeijer, J., Dahlbom, M., Macpherson, B., Ballard, S., Inverarity, G., Carley, J., Alexander, C., Dowell, D., Liu, S., Ikuta, Y. and Fujita, T. (2018) Survey of data assimilation methods for convective-scale numerical weather prediction at operational centres. *Quarterly Journal of the Royal Meteorological Society*, 144(713), 1218–1256.

Haiden, T., Janousek, M., Vitart, F., Ferranti, L. and Prates, F. (2019) Evaluation of ECMWF forecasts, including the 2019 upgrade. Technical Memorandum, European Centre for Medium-Range Weather Forecasts 853. Reading, UK: ECMWF.

Hou, A.Y., Kakar, R.K., Neeck, S., Azarbarzin, A.A., Kummerow, C.D., Kojima, M., Oki, R., Nakamura, K. and Iiguchi, T. (2014) The global precipitation measurement mission. *Bulletin of the American Meteorological Society*, 95, 701–722.

Huang, X.-Y., Barker, D., Webster, S., Dipankar, A., Lock, A., Mittermaier, M., Sun, X., North, R., Darvell, R., Boyd, D., Lo, J., Liu, J., Macpherson, B., Heng, P., Maycock, A., Pitcher, L., Tubbs, B., McMillan, M., Zhang, S., Hagelin, S., Porson, A., Song, G., Beckett, B., Cheong, W.K., Semple, A. and Gordon, C. (2019) SINGV – the convective-scale numerical weather prediction system for Singapore. *ASEAN Journal on Science and Technology for Development*, 36(3), 81–90.

Ingleby, N.B., Lorenc, A.C., Negan, K., Rawlins, F. and Jackson, D.R. (2013) Improved variational analyses using a nonlinear humidity control variable. *Quarterly Journal of the Royal Meteorological Society*, 139(676), 1875–1887.

Jackson, D.R., Keil, M. and Devenish, B.J. (2008) Use of Canadian quick covariances in the Met Office data assimilation system. *Quarterly Journal of the Royal Meteorological Society*, 134, 1567–1582.

Lean, H.W., Clark, P.A., Dixon, M., Roberts, N.M., Fitch, A., Forbes, R. and Halliwell, C. (2008) Characteristics of high-resolution versions of the Met Office Unified Model for forecasting convection over the United Kingdom. *Monthly Weather Review*, 136, 3408–3424.

Lorenc, A.C. and Marriott, R.T. (2014) Forecast sensitivity to observations in the Met Office Global numerical weather prediction system. *Quarterly Journal of the Royal Meteorological Society*, 140, 209–224.

National Environment Agency. (2009) *Weatherwise Singapore*. Singapore: Meteorological Services Division, National Environment Agency.

Parrish, D.F. and Derber, J.C. (1992) The National Meteorological Center’s spectral statistical interpolation analysis system. *Monthly Weather Review*, 120, 1747–1763.

Pavelin, E.G., English, S.J. and Eyre, J.R. (2008) The assimilation of cloud-aﬀected infrared satellite radiances for numerical weather prediction. *Quarterly Journal of the Royal Meteorological Society*, 134, 737–749.

Rainwater, S., Bishop, C.H. and Campbell, W.F. (2015) The benefits of correlated observation errors for small scales. *Quarterly Journal of the Royal Meteorological Society*, 141(693), 3439–3445.

Renshaw, R. and Francis, P.N. (2011) Variational assimilation of cloud fraction in the operational Met Office Unified Model. *Quarterly Journal of the Royal Meteorological Society*, 137, 1963–1974.

Roberts, N.M. and Lean, H.W. (2007) Scale-selective verification of rainfall accumulations from high-resolution forecasts of convective events. *Monthly Weather Review*, 136, 78–97.

Široká, M., Fischer, C., Cassé, V., Brožková, R. and Geleyn, J.-F. (2003) The definition of mesoscale selective forecast error covariances for a limited area variational analysis. *Meteorology and Atmospheric Physics*, 82, 227–244.

Strajnar, B. (2012) Validation of mode-S meteorological routine air report aircraft observations. *Journal of Geophysical Research*, 117(D23), D23110.

Sun, J., Trier, S.B., Xiao, Q., Weisman, M.L., Wang, H., Ying, Z., Xu, M. and Zhang, Y. (2012) Sensitivity of 0–12-h warm-season
precipitation forecasts over the central United States to model initialization. *Weather and Forecasting*, 27, 832–855.

Tang, Y., Lean, H.W. and Bornemann, J. (2013) The benefits of the Met Office variable resolution NWP model for forecasting convection. *Meteorological Applications*, 20, 417–426.

Vetra-Carvalho, S., Dixon, M., Migliorini, S., Nichols, N.K. and Ballard, S.P. (2012) Breakdown of hydrostatic balance at convective scales in the forecast errors in the Met Office Unified Model. *Quarterly Journal of the Royal Meteorological Society*, 138(668), 1709–1720.

Wang, H., Huang, X.-Y., Xu, D. and Liu, J. (2014) A scale-dependent blending scheme for WRFDA: impact on regional weather forecasting. *Geoscientific Model Development*, 7, 1819–1828.

Weller, E., Shelton, K., Reeder, M.J. and Jakob, C. (2017) Precipitation associated with convergence lines. *Journal of Climate*, 30, 3169–3183.

Wlasak, M.A. and Cullen, M.J.P. (2014) Modelling static 3-D spatial background error covariances – the effect of vertical and horizontal transform order. *Advances in Science and Research*, 11, 63–67.

Zagar, N., Gustafsson, N. and Källén, E. (2004) Variational data assimilation in the Tropics: the impact of background-error constraint. *Quarterly Journal of the Royal Meteorological Society*, 130, 103–125.

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