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Improving (Very) Short Range Precipitation Forecasting in New Zealand

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Supervisor: Geoff Austin

A thesis submitted in fulfilment of the requirements for the degree of Doctor of Philosophy in the

Atmospheric Physics Group
Department of Physics

November 2015
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Abstract

(Very) short range quantitative precipitation forecasting (QPF) plays an important role in both meteorological and hydrological risk management. Since New Zealand is an island country, which is surrounded by the Tasman Sea and South Pacific Ocean, most high impact weather systems, especially heavy rainfall systems, usually initiate and develop in the regions where there are no direct high resolution observations. Using satellite rainfall and cloudiness estimates to couple with the observations from the National Radar Network becomes crucial.

This thesis makes use of satellite data coupled with observations from the National Radar Network for the initialization of a mesoscale forecast model for the region. To achieve this we employed a technique called “RainSat” to delineate precipitation maps in the regions beyond radar range. The errors associated with the “RainSat” technique include the accuracy of the statistical technique itself, sampling errors, height assignment, and the estimates of rain rates. These errors and the impacts on the forecast model have been investigated in Chapter 2 and 3 of the thesis. It has been found that, in spite of these significant errors, the “RainSat” technique is able to provide relatively useful estimates of precipitation out to a range of 200 km beyond radar maximum range.

Besides the capability of extending the availability of the precipitation observations to the Tasman Sea, the “RainSat” technique has been used as additional data with the observed radar reflectivity for improving nowcasting in New Zealand (Chapter 4). The results showed that the combination of radar reflectivity and satellite retrieved rain rates can significantly reduce the uncertainties in the extrapolation based techniques that are caused by the incomplete echoes observed by radar alone in areas near the edge of the radar coverage area. According to our experiments, the improvements led by using the additional “RainSat” analysis became more obvious as the lead time increased. However, the skill was still very limited after 2-3 hours.

Data assimilation experiments with radar and satellite data in New Zealand are introduced in Chapters 5-8. In order to incorporate radar (satellite) observed rainfall information with modest computing facilities, a new nudging based scheme has been introduced in Chapter 5. The new scheme uses the reverse Kessler warm rain processes and the associated saturation adjustment. The statistical scores showed that, by assimilating radar reflectivity data in the
model using the new scheme, precipitation forecasts could be improved up to 7-9 hours ahead on average compared to the dynamic downscaling experiments.

Since the assimilation operator developed in this thesis only uses a simplistic liquid phase microphysics scheme, the skill of the operator with more complicated model microphysics in the model were presented (Chapter 6). The results showed that different cloud physics schemes adopted within the time window have significant effects on the precipitation forecasting whilst showing minimal effects on wind corrections. According to our experiments, the use of the WRF Lin et al. scheme coupled with the RK-nudging approach might give the highest skill score on average during the nudging time window.

For New Zealand, high impact weather systems usually initiate and develop in regions that are beyond radar range, which means that some sort of satellite technique is particularly important for these events. In addition, the model background usually presents inaccurate estimates over the oceanic areas. Therefore, the incorporation of satellite retrieved moisture fields over the Tasman Sea is expected to be beneficial to the (very) short range precipitation forecasting in New Zealand. The assimilation experiments of the “RainSat” analysis are presented in Chapter 7. The newly developed scheme and the Water Vapour Correction (WVC) scheme have been employed and the verifications were carried out against to both radar and TRMM Multi-Satellite Precipitation Analysis using different objective scoring schemes. The results indicated that by using the satellite rainfall and cloudiness estimates to adjust the moisture fields out of the radar range, the precipitation forecasts could be further improved.

In Chapter 8, the extrapolated rain rates generated from both radar and satellite data were used to adjust the corresponding model background. The results showed that the assimilation of radar and satellite based nowcasting data could effectively prolong the effects of the initial conditions in the NWP model and thus improve the precipitation forecasts even further. A brief conclusion is given in Chapter 9.

**Key words:** RainSat, nowcasting, precipitation, data assimilation, radar, nudging, NWP
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Figure 1: Concept map of the thesis

Chapter 1. Introduction

Chapter 2. Implementing the “RainSat” technique for improving precipitation observations in New Zealand

Chapter 3. Errors inherent in the “RainSat” technique

Chapter 4. Combining radar and satellite data to improve nowcasting

Chapter 5. The implementation of reverse Kessler warm rain scheme for radar reflectivity assimilation using a nudging approach in New Zealand

Chapter 6. The application of the RK-nudging approach with different microphysics schemes in the model

Chapter 7. The effects of the assimilation of satellite retrieved clouds and precipitation on (very) short-range precipitation forecasting in New Zealand

Chapter 8. Using nowcasting data to initialize high resolution NWP model for improving precipitation forecasting in New Zealand

Chapter 9. Conclusions

Motivations:

Chapter 2:
[1] Most high impact weather system initialize and develop over the Tasman Sea;
[2] The National Radar Network can only provide high resolution observations about 200 km (maximum) out of the coast

Chapter 3:
Investigate the errors inherent in the “RainSat” technique

Chapter 4:
[1] Considerable errors may exist if we use incomplete radar echoes for nowcasting;
[2] The “RainSat” analyses usually have the highest correlation coefficients to the associated radar reflectivity map

Chapter 5:
[1] The linearisation error is significant in WRF 3D-Var reflectivity forward operator
[2] Countries like New Zealand do not have massive computational resources available
[3] LHN may introduce errors at “dry” grid points;

Chapter 6:
RK-nudging is developed based on the simple Kessler scheme, while most models adopt more complicated multi-phases physics processes for their microphysics scheme

Chapter 7:
[1] High impact rainfall systems for New Zealand usually develop from the area out of the radar range;
[2] Model is usually not able to provide accurate precipitation related fields over the Tasman Sea;
[3] It is essential to improve the capability of offshore precipitation forecasts

Chapter 8:
[1] Overall, extrapolation based nowcasting is capable of providing better very short range precipitation estimates compared to NWP models
[2] The assimilation of nowcasting data may prolong the effects of the improved initial conditions
Figure 2: The Auckland University Integrated Forecasting System (Test Platform).

The NWP model was run using the small group cluster (The system comprised of 16 dual core E8600 Intel based personal computers). The computational facilities provided by National eScience Infrastructure (NeSI) were used to replace the group cluster from the end of 2013. GOES Imager data were obtained from NOAA Comprehensive Large Array-Data Stewardship System (CLASS). Radar data were provided by New Zealand Meteorological Service Ltd. (NZ MetService) under the agreement between the Atmospheric Physics Group (UOA) and MetService. NCEP Final Analysis Data (FNL) were provided by CISL Research Data Archive. WRF-ARW and the associated 3D-Var radar reflectivity forward operator are provided by NCAR and UCAR under the free license attached.
Contents

Abstract ................................................................................................................................... I
Acknowledgements .............................................................................................................. III
Figure 1: Concept map of the thesis ...................................................................................... a
Figure 2: The Auckland University Integrated Forecasting System (Test Platform). .......... b
Chapter 1. Introduction .......................................................................................................... 1
  1.1 Introduction .................................................................................................................. 1
  1.2 Numerical models and the associated clouds/precipitation data assimilation schemes
      used operationally .............................................................................................................. 2
  1.3 A short review of extrapolation based nowcasting ...................................................... 7
  1.4 New Zealand precipitation distributions and the national precipitation observation
      network ............................................................................................................................... 9
  1.5 Spatial resolution dependant objective skill scores ................................................ 14
  1.6 Challenges and opportunities of New Zealand precipitation forecasts ............ 15
  1.7 Research objectives .................................................................................................... 17
  1.8 Organization of the thesis ........................................................................................... 18
Chapter 2. Implementing the “RainSat” technique for improving precipitation observations
      in New Zealand .................................................................................................................... 19
  2.1 Abstract ...................................................................................................................... 19
  2.2 Introduction ................................................................................................................ 19
  2.3 Satellite precipitation measurements .......................................................................... 20
  2.4 The implementation of the “RainSat” technique in New Zealand ............................. 24
  2.5 “RainSat” based nowcasting experiments in New Zealand ....................................... 26
  2.6 Conclusions ................................................................................................................ 28
Chapter 3. Errors inherent in the “RainSat” technique ........................................................ 30
  3.1 Abstract ...................................................................................................................... 30
  3.2 Introduction ................................................................................................................ 30
  3.3 Regression issues ........................................................................................................ 32
  3.4 Spatial sampling related errors ................................................................................... 35
      3.4.1. The impact of spatial resolution on “RainSat” rainfall delineation ....................... 37
      3.4.2. The effect of the spatial scale of satellite data on “RainSat” based nowcasting.... 39
  3.5 The height of the “RainSat” retrieved precipitation ................................................... 41
Chapter 8. Using nowcasting data to initialize high resolution NWP model for improving precipitation forecasting in New Zealand

8.1 Abstract .................................................................................................................. 102
8.2 Introduction ............................................................................................................. 102
8.3 Methodology .......................................................................................................... 104
  8.3.1 Data assimilation scheme .................................................................................. 104
  8.3.2 Nowcasting ....................................................................................................... 104
  8.3.3 Model configurations ....................................................................................... 105
8.4 Results and Discussions ........................................................................................ 106
  8.4.1 Detailed case study .......................................................................................... 106
  8.4.2 Combined skill scores ..................................................................................... 110
8.5 Conclusions ............................................................................................................ 114

9. Conclusions .............................................................................................................. 116

Appendix A. Verification Skill Scores ........................................................................ 122
Appendix B. Details of the implementation of the RK-nudging codes in WRF .......... 125
Bibliography ................................................................................................................ 130
Figure 1.2: Wellington C-band radar operated by NZ MetService (photo obtained from Shucksmith (2013)).

Figure 1.3: A simulated cell (left) and the corresponding observation (right).

Figure 2.1: Location of New Zealand and the surrounding nations. Geography dataset is provided by GSHHG (Global Self-consistent, Hierarchical, High-resolution Geography Dataset).

Figure 2.2: The analysis of surface pressure obtained at 1300 NZT 04 November 2013 and 0700 NZT 05 November 2013. Weather charts were provided by New Zealand MetService Ltd.

Figure 2.3: The procedure of deriving rainfall probability with the “RainSat” technique has been adapted from Bellon et al. (1980). $V_{nr}$ and $V_r$ indicate the visible radiances corresponding to the areas without and with radar observed reflectivity, respectively. $IR_{nr}$ and $IR_r$ are similar to $V_{nr}$ and $V_r$ but indicate the infrared radiances. $R_{nr}$ and $R_r$ represent the radar reflectivity corresponding to rain/non-rain areas. $P_{rs}$ indicates the probability of rain matrix as a function of VIS and IR.

Figure 2.4: The illustration of the “RainSat” based extrapolation scheme. In the thesis, the extrapolated visible and infrared imageries (represented by VIS' and IR', respectively) are coupled with the radar based nowcast (RADAR') to produce the “RainSat” based nowcasts for subsequent hours.

Figure 2.5: Top-left: VIS imagery; top-right: IR imagery; bottom-right: the “RainSat” derived probability map (The range of optimal probability threshold is between 60% and 100%); bottom-left: corresponding radar observed reflectivity (unit: dBZ). Data were obtained at 0000 UTC 30 December 2011.

Figure 2.6: S scores calculated by Equation 2.2 for different selected probabilities. Here both $a$ and $b$ are set equally to 0.5. The radar threshold for calculating the scores were set to 15 dBZ.

Figure 2.7: Combined CSI and FAR skill scores for the “RainSat” based nowcasts. The verifications were carried out within the range of New Zealand National Radar Network. Due to the decreased size of bivariate frequency distributions table, FAR also decreased with the lead time increased. Unskilled skill scores were calculated based on the combined skill scores for radar based nowcasting at 6 hours (The unskilled reference CSI and FAR are 0.02408 and 0.81301, respectively).

Figure 2.8: Combined CSI and FAR Skill scores for the radar based nowcasts.

Figure 2.9: Right-bottom: observed radar reflectivity at 0000 UTC 01 November 2013 (T+1); Left-bottom: 1 h nowcasting (T+1) from radar echoes extrapolation; Top: 1 h nowcasting (T+1) from the “RainSat” extrapolated probability.

Figure 3.1: CSI (top) and FAR (bottom) scores for the “RainSat” retrieved rainfall probability in terms of the distance between verification area and the selected radar (unskilled CSI: 0.02408; unskilled FAR: 0.81301).
Figure 3.2: CSI (top) and FAR (bottom) scores for the extrapolated “RainSat” probability map (1h: left; 2h: middle; 3h: right column) in terms of the distance between verification area and the selected single radar station (unskilled CSI: 0.02408; unskilled FAR: 0.81301).

Figure 3.3: Probability distributions ( > 0% ) as a function of VIS (indicated by horizontal axis) and IR (indicated by vertical axis) radiances obtained from GOES satellite for the case at 0000 UTC 30 December 2011. The resolution of satellite data was spatial averaged to 10 × 10 km (top) and 50 × 50 km (bottom).

Figure 3.4a: Skill scores as a function of spatial resolution of satellite data. The “RainSat” retrieved rainfall maps were obtained using all radars of New Zealand National Radar Network, and verification was carried out within the radar range. Horizontal and vertical axes indicate the spatial resolutions and the associated scores, respectively.

Figure 3.4b: Same as Figure 3.4a but with single radar as the “ground truth”.

Figure 3.5: NRMSE in terms of intensity (top) and probability (bottom). All radars of National Radar Network were used to be the “ground truth”. Horizontal and vertical axes indicate the selected resolutions (km) and NRMSE scores, respectively.

Figure 3.6: Skill scores as a function of spatial resolution of satellite data. Vertical and horizontal axes indicate resolutions and the associated scores: correlation coefficient (left-top), Frequency Bias index (right-top), RMSE – intensity (left-bottom) and RMSE – probability (right-bottom).

Figure 3.7: Average spatial - temporal NRMSE contours for the “RainSat” based nowcasting. Horizontal and vertical axes indicate different resolutions and lead times (min), respectively.

Figure 3.8: Normalized standard deviation (NSTD) of different skill scores (vertical axis) as a function of forecast lead time (horizontal axis).

Figure 3.9: The comparisons between the temperatures (0000 UTC 04 December 2011) obtained from WRF, radio sounding and satellite (Cloud Top Temperature). The data was obtained at (174.62, -36.79), where is the location of Auckland Aero Station.

Figure 3.10: Radar retrieved echo top height (ETH) and satellite retrieved cloud top height (CTH) obtained at 0000 UTC 01 November 2011, 0000 UTC 31 December 2011, 0000 UTC 07 January 2012. Radar stations selected to retrieve the ETH are AKL, NPL, BOP and AKL, respectively. The satellite retrieved height for the dBZ free area was set to zero.

Figure 3.11: The average distributions of the height difference calculated over all selected cases.

Figure 3.12: The distributions of the height difference in terms of the different distances from radar station ranging from 50 km to 200 km.

Figure 3.13: Average WRF height difference (m) calculated between two adjunct layers at 0000 UTC 21 November 2011.
Figure 3.14: The Correlation Coefficients (CC) calculated for each selected case at the threshold of 0.02 $mm\ h^{-1}$. ................................................................. 172

Figure 3.15: The scores of RMSE, MAE and FBI calculated for each selected case at the threshold of 0.02 $mm\ h^{-1}$. ......................................................................................... 173

Figure 3.16: The scores of RMSE, MAE and FBI calculated for each selected case at the threshold of 0.5 $mm\ h^{-1}$. ................................................................. 174

Figure 3.17: The scores of RMSE, MAE and FBI calculated for each selected case at the threshold of 2.0 $mm\ h^{-1}$. ......................................................................................... 175

Figure 4.1: Errors resulted by using the incomplete echoes obtained by radar for extrapolation based precipitation nowcasting. ................................................. 176

Figure 4.2: Errors resulted by the incomplete echoes obtained by radar for extrapolation based precipitation nowcasting. ................................................. 176

Figure 4.3: The scheme for combining radar and satellite data for nowcasting. ...... 177

“Sat_cell1”, “Sat_cell2” and “Sat_cell3” represent three individual cells recognized from the “RainSat” analysis. “Rad_cell1” and “Rad_cell2” are two cells recognized from radar. “Sat_cell1” and “Sat_cell2” are the proportions of cells in the radar range corresponding to “Sat_cell1” and “Sat_cell2”, respectively. ........................................... 177

Figure 4.4: Radar, the “RainSat” analysis and the combined analysis obtained at 2300 UTC 31 October 2011 and 0000 UTC 01 November 2011. Extrapolation based nowcasts were generated based on the analysis at these images. ......................... 177

Figure 4.5: Motion vectors retrieved from radar images and the combined analysis for Case 1. In order to show the vectors clear, the resolution of the retrieved motion vectors was smoothed to 15 km. ................................................................. 178

Figure 4.6: Case 1: The comparisons of radar alone extrapolation (left) and the “radar+Rainsat” based extrapolation (middle) with the associated observations (right) from lead times from 1 h to 3 h. ................................................................. 179

Figure 4.7: The absolute mean bias of dBZ weighted echo centres between observed and extrapolated precipitation in terms of the threshold of 15 dBZ for Case 1. .................. 180

Figure 4.8: The absolute mean bias of echo area between observed and extrapolated precipitation in terms of the threshold of 15 dBZ for Case 1.............................. 180

Figure 4.9: Probability of Detection (POD), Equitable Threat Score (ETS), False Alarm Ratio (FAR) and Frequency Bias index (FBI) scores for Case 1 over 6 hours. .............. 181

Figure 4.10: Radar (left), the “RainSat” analysis (middle) and the combined analysis (right) obtained at 2300 UTC 06 January 2012 and 0000 UTC 07 January 2012. Extrapolation based nowcasting for Case 2 were generated based on the analysis at these images. .................................................................................................. 182
Figure 4.11: Motion vectors retrieved from radar images and the combined analysis for Case 2. In order to show the vectors clear, the resolution of the retrieved motion vectors was smoothed to 15 km. ................................................................. 182

Figure 4.12: The comparisons of radar alone extrapolation and the “radar+Rainsat” based extrapolation with the associated observations from the lead time of 1 h to 3 h for Case 2. ................................................................. 183

Figure 4.13: The mean absolute bias of dBZ weighted echo centres between observed and extrapolated precipitation in terms of the threshold of 15 dBZ for Case 2. ................. 184

Figure 4.14: The mean absolute bias of echo area between observed and extrapolated precipitation in terms of the threshold of 15 dBZ for Case 2. ........................................ 184

Figure 4.15: Probability of Detection (POD), Equitable Threat Score (ETS), False Alarm Ratio (FAR) and Frequency Bias Index (FBI) scores for Case 2 over 6 hours. ................................................ 185

Figure 5.1: Experimental designs for all selected cases. CTL run: initialized with previous 3 h free forecasts; DA run: initialized with radar reflectivity and previous 3 h forecasts. ................................................................. 186

Figure 5.2: Phase changes of radar observed reflectivity (dBZ) at 0300 (T+0), 0315 (T+15min) and 0330 (T+30min) UTC 01 November 2011. .................................................. 186

Figure 5.3: Model outer domain (D01) and inner domain (D02) adopted in this study. The spatial resolutions for D01 and D02 are 9 km and 3 km, respectively. ..................... 187

Figure 5.4: Combined ETS scores in terms of different thresholds and lead hours. Horizontal axis indicates forecast lead hours and vertical axis indicates the average scores. Verification thresholds: 0.5 mm h\(^{-1}\) (top-left), 1.0 mm h\(^{-1}\) (top-right), 2.0 mm h\(^{-1}\) (bottom-left) and 5.0 mm h\(^{-1}\) (bottom-right). .................................................. 188

Figure 5.5: Same as Figure 5.4 but with FAR scores. ................................................ 189

Figure 5.6: Same as Figure 5.4 but with FSS scores in terms of different thresholds and scales (Dash line: DA; Solid line: CTL). ................................................................. 190

Figure 5.7: MSLP analysis (Manual) obtained from Bureau of Meteorology, Australia (top) and the associated WRF simulated MSLP analysis (bottom) at 0000 UTC 01 November 2011. ................................................................. 191

Figure 5.8: Hourly accumulated precipitation (mm) for the case of 01 November 2011 at 0400 UTC (first row), 0500 UTC (second row), 0600 UTC (third row). CTL runs (left column), DA runs (middle column) and the associated radar observations (right column) are plotted with the threshold of 0.05 mm h\(^{-1}\). A-B indicates the position of the vertical cross section shown in Figure 5.9. ................................................................. 192

Figure 5.9: Vertical cross section (the position of the vertical cross-section is shown in Figure 5.8) of simulated rain water (kg kg\(^{-1}\)) (shaded) and vertical winds (m s\(^{-1}\)) (in black solid contour) at 0400 UTC 01 November 2011 for the CTL run (top) and the DA run (bottom). Black dot contour indicates the height (m) at each model level. .................... 193
Figure 5.10: The distributions of maximum rain water (g kg\(^{-1}\)) for the CTL run (horizontal axis) and DA run (vertical axis) at (T+1), which was 30 minutes after the end of the obs-nudging time window. Left: it shows the situation where assimilated radar derived rain water was larger than the model backgrounds at (T+0). Right: shows the opposite situation where the assimilated derived rain water was smaller than the model backgrounds at (T+0). The relative frequency of “Obs > Model” vs “Obs < model” for this case is 1.76.

Figure 5.11: The comparisons between \(\Delta q_v\) and the corresponding \(\Delta q_r\) at 0300 UTC 01 November 2011 (\(\Delta q_v\) and \(\Delta q_r\) were calculated by the reverse Kessler scheme but have not been assimilated into the model by nudging approach). Top: \(\Delta q_r > 0\). Bottom: \(\Delta q_r < 0\).

Figure 5.12: The simulated maximum rain water in a column for the DA run (bottom-left) and the CTL run (bottom-right) and the associated radar derived rain water (top) at 0400 UTC 01 November 2011 (threshold: \(0.2 \times 10^{-3}\) kg kg\(^{-1}\)).

Figure 6.1: Land stations used for the verifications for surface temperature and wind.

Figure 6.2: Averaged OMF (observation - forecast) of temperature at (T+1h, 30 minutes after the DA window) over all selected cases for different microphysics schemes in the model. The window for RK-nudging was set to 30 minutes from T+0h to T+30min. (Since there are no observations at T+30mins, 30 minutes lag were given for the verifications).

Figure 6.3: Averaged OMF (observation - forecast) of temperature at (T+1h, 30 minutes after the DA window) over all stations. X-axis indicates the case number and y-axis shows the bias.

Figure 6.4: Same to Figure 6.2 but with U winds.

Figure 6.5: Same to Figure 6.2 but with V winds.

Figure 6.6: POD, ETS and FAR at (T+1h, 30 minutes after the DA window) at different thresholds for different cases. X and y axises indicate the case number and the forecast skills, respectively. Thresholds were ranged between 0.05 mm h\(^{-1}\) and 2.0 mm h\(^{-1}\).

Figure 7.1: Retrieved precipitation areas using IR alone technique (left), the “RainSat” technique and the associated radar data for 0000 UTC 01 November 2011 (top) and 0000 UTC 31 December 2011 (bottom). Here, the IR alone technique is adopted based on the approach described by Kidder et al., (2005).

Figure 7.2: the vertical distribution of \(w(z_i)\) function adopted by Sokol (2010). This distribution was applied in all the WVC related experiments in this chapter.

Figure 7.3: Vertical cross sections of cloud water (shaded), rain water (black line) and water vapour mixing ratio (grey line) for Case 1 (top) and 2 (bottom). The units for all the three selected fields are kg kg\(^{-1}\).
Figure 7.4: Vertical cross sections (at 35.5°S) of cloud water (shaded), rain water (black line) and water vapour mixing ratio (grey line) obtained at 01 UTC of Case 1 (30 min after the data assimilation window). The units for all the three selected fields are $kg \cdot kg^{-1}$. ........................................................................................................................................ 205

Figure 7.5: Vertical slice of (Control – WVC-radar) in terms of cloud water and rain water for Case 1 (top) and Case 2 (bottom). .......................................................................................... 206

Figure 7.6: Precipitation forecasts on 01 November 2011 with the threshold of 0.02 mm h$^{-1}$. From left to right: radar observations, CTL, RK-Radar, RK-RadSat, RK-RadCld and WVC-radar+RainSat. CTL indicates the simulations without the initialization by high resolution data. ............................................................................. 207

Figure 7.7: Same to Figure 7.4 but for Case 2, and at the latitude of 35°S .......... 208

Figure 7.8: Precipitation forecasts on 31 December 2011 with the threshold of 0.02 mm h$^{-1}$. From left to right: radar observations, CTL, RK-Radar, RK-RadSat, RK-RadCld and WVC-radar+RainSat. CTL indicates the simulations without the initialization with high resolution data. .......................................................................... 209

Figure 7.9.: Combined POD, ETS and FAR scores for all selected cases in terms of different thresholds. All scores were calculated at the spatial scale of 3.0 km over the whole New Zealand. “Solid line”: Control experiment; “+”: RK-Radar; “o”: RK-RadSat; “*”: RK-RadCld; “x”: WVC-radar; “□”: WVC-RadCld; “◊”: WVC-RadSat. X and y axes indicate the lead time and skill scores, respectively. ............................................. 210

Figure 7.10: Average Fractional Skill Scores (FSS) in terms of different thresholds and spatial scales. “Solid line”: Control experiment; “+”: RK-Radar; “o”: RK-RadSat; “*”: RK-RadCld; “x”: WVC-radar; “□”: WVC-RadCld; “◊”: WVC-RadSat. .......................... 211

Figure 7.11: Combined POD scores in terms of different thresholds over the Tasman Sea for a total of 13 cases................................................................. 212

Figure 7.12: Combined ETS scores in terms of different thresholds over the Tasman Sea for a total of 13 cases................................................................. 213

Figure 7.13: Combined FAR scores in terms of different thresholds over the Tasman Sea for a total of 13 cases................................................................. 214

Figure 8.1: Concept of the skills of different forecast schemes. Solid line and dashed line indicate the skill of NWP initialized without and with high resolution radar observations, respectively. Dash-dot line indicates the skill of nowcasting and dot line indicates the skill of NWP initialized with both observation and nowcasting data at T+0 and T+1, respectively................................................................. 215

Figure 8.2: Experimental design: 1) “Radar”: only observed radar reflectivity was assimilated; (2) “Radar+RainSat”: both the observed radar reflectivity and the “RainSat” analysis were assimilated; (3) “Ext-Radar”: both the observed and extrapolated radar reflectivity were assimilated; (4) “Ext-Radar+RainSat”: the assimilation of the observed and extrapolated radar reflectivity and the “RainSat” analysis......................................................... 215
Figure 8.3: Mean Sea Level Pressure (MSLP) manual analysis for Australian Region at 18 UTC 06 January 2012 (obtained from Bureau of Meteorology, Australia) .......... 216

Figure 8.4: Radar observations and the associated simulations with different assimilation configurations for 0200 - 0400 UTC 07 January 2011. Observation and nowcasting data were assimilated at 00 and 01 UTC, respectively. ......................................................... 217

Figure 8.5: Three hours (0200 – 0400 UTC 07 January 2012) simulated precipitation accumulations for different data assimilation schemes and the associated observations (top-left). ........................................................................................................................ 218

Figure 8.6: Combined forecast skill scores (POD, ETS and FAR) for the event of 07 January 2012. “Solid line”: “Control”; “+”: “Radar”; “◦”: “Ext-Radar”; “∗”: “Radar+RainSat”; “*”: “Ext-Radar+RainSat”. ............................................................. 219

Figure 8.7: Combined skill scores (POD, ETS and FAR) in terms of different thresholds. “Solid line”: “Control”; “+”: “Radar”; “◦”: “Radar+RainSat”, “∗”: “Radar”, “Δ”: “Ext-Radar+RainSat”. (The verifications were begun at the lead time 1 hour). ..................... 220

Figure 8.8: Average correlation coefficients for different forecast schemes (The verifications were begun at the lead time of 1 h). .......................................................... 221

Figure 8.9: Combined Fractional Skill Scores (FSS) for different forecast schemes in terms of different thresholds. “Red”: “Control”; “Green”: “Radar”; “Blue”: “Ext-Radar”; “Cyan”: “Radar+RainSat”; “Magenta”: “Ext-Radar+RainSat”; “Black”: “Nowcasting”; X and y axes indicate lead time and the skill scores, respectively................................. 222
Chapter 1. Introduction

1.1 Introduction

Very short range precipitation forecasting usually refers to the 0-12 h descriptions of the initiation and development of precipitation. The forecasting for the first 0-2 h is also refereed as “nowcasting”, which includes the prediction of high impact weather events using extrapolation based techniques (Wilson et al., 1998; Ruzanski, 2010; Austin et al., 2012). After a specific period (e.g., 2 hours), the development/decay of precipitation, either in pattern, intensity or curved trajectory, usually leads to significant errors for the forecast based on simple linear extrapolation approaches (Wilson et al., 1998). Therefore, besides the persistence/trends method (e.g., radar echo extrapolation) and the insight from climatology and analog matching methods (e.g., the weather is predicted as the same as it did on some previous occasion considering all available synoptic characteristics), numerical weather prediction (NWP) model plays an essential role for precipitation forecasts between 2-12 hours (e.g., Sasaki, 1955; Kalnay, 2003). In recent years, the blending of traditional extrapolation based techniques with high resolution NWP model provides an opportunity to improve 0-6 h precipitation forecasts further. However, currently the accuracy of the very short range precipitation forecasting is constrained by many factors, for example, the predictability of different types of weather systems, microphysics and dynamical parameterization schemes adopted in the model and the sampling errors of model and observations. For an island country like New Zealand, the lack of high resolution observations over the sea is also a significant problem. Overall, for most operational centres around the world, the combination of nowcasting, NWP model and manual analysis are still widely used for providing precipitation forecasts at present, although there are still many inherent uncertainties and errors and some of them are very difficult to be addressed in the near future (Wilson et al., 1998; Austin et al., 2012; Sokol and Zacharov, 2012; Sun et al., 2013).

Traditional manual analysis is still widely used and it is usually carried out based on the relationship between rainfall and other fields of the atmosphere such as moist air masses, orographic uplift and low pressure centres. Relatively large scale precipitation patterns and the associated intensity usually can be estimated well up to several days ahead using the manual analysis with the guidance of global model outputs. On the convective scale,
thermodynamic diagrams representing atmospheric profiles are usually used to estimate the associated energies. In most cases, analysis according to historical data also plays a very important role in the traditional manual forecasting techniques (Lynch, 2006).

NWP models, especially mesoscale models, have experienced significant development during last several decades and at present, the use of NWP models gradually becomes essential in precipitation forecasting in most countries. Nowadays, non-hydrostatic models have been developed and applied for resolving small scale meteorological phenomena at the spatial resolution of a few kilometres (Lynch, 2011). Besides mesoscale models, global modeling systems, which usually including the assimilation of low resolution but globally coverage data such as satellite imagery and soundings, are also operated in many operational centres. These global systems, although they might not be able to provide very accurate mesoscale precipitation forecasts, considering their spatial resolution, they dramatically increase the useful range of NWP precipitation forecasts and their analyses can be used as the initial conditions for mesoscale models.

For the forecasts with a lead time of less than a few hours, radar reflectivity echoes and the associated extrapolation techniques are usually used. Traditional extrapolation techniques are usually developed based on area-based methods, which estimate one or multiple motion vectors over the entire radar coverage area. Object-based extrapolation methods, which couple with the recognition of rainfall features, are usually developed along with the area-based methods. More advanced techniques, like stochastic methods or the hybrid methods with NWP models have also been introduced during recent years (e.g., Austin and Bellon, 1974; Austin et al., 1987; Ruzanski, 2010).

In this thesis, considering the growth of the public need for very short range precipitation forecasts, we have focused on the issues involving NWP models and nowcasting for New Zealand. However, the issues discussed and investigated here can be applied to other similar island countries or to the coastal regions of other countries as well.

1.2 Numerical models and the associated clouds/precipitation data assimilation schemes used operationally

Numerical models, especially the model systems designed for resolving mesoscale
convective activity, have been very important tools for weather forecasting over the past several decades. The basic ideas of NWP were developed about 100 years ago, although at that time there were no appropriate computing facilities available. The development of the understanding of atmospheric dynamics and microphysical processes before the first digital computer provided the necessary understanding for the development of actual NWP in the future. The first meteorologist who raised the concept of NWP is Cleveland Abbe, as he developed a set of equations to characterise the atmosphere (Abbe, 1901). Similar approaches were also developed and discussed by Bjerknes (1904) with analysis that is more detailed.

After that, the attempts at solving the equations for atmospheric motion were made by Richardson (1922). However, due to the imbalanced initial conditions used, the prediction made by Richardson was unrealistic. Moreover, considering the digital computer was not yet invented, the forecast scheme presented by Richardson was quite impractical. The details of Richardson’s scheme have been reviewed by Lynch (2006). It is worth noting that the main contribution of Richardson (1922) is that it first described the “analog approach” which is still widely used in operational forecasting today. Lynch (2011) gives the four key elements for the development of NWP after the Richardson’s scheme: (1) the understanding of atmospheric dynamics and microphysics processes is improved with the developments in the theory of meteorology; (2) More advanced mathematical analysis led to more stable and accurate solutions for numerical equations; (3) three dimensions observations became available and (4) the development of computing facilities.

During last two decades, a number of numerical models were widely used around the world to meet the requirement of better predictions for public. Most of them are non-hydrostatic models and some of them have been applied to operational NWP for many years. In Europe, UK MetOffice (UKMO) is the first operational centre which applied a non-hydrostatic model operationally. The UKMO Mesoscale Model, which was developed based on the model designed by Tapp and White (1976), has been operationally run over 8 years from 1985 to 1993. The UKMO Mesoscale Model was then replaced by the Unified Model (UM) (Cullen, 1990; Staniforth and Cote, 1991; Davies et al., 2005). It is worth mentioning that both the regional and global schemes for UM are performed using non-hydrostatic cores, which makes UM the world first global non-hydrostatic model implemented operationally. Other than UK, UM is also widely used in other countries like
Chapter 1. Introduction

Australia, Korea, India, Norway and New Zealand.

Apart from UM, several other Limited Area Models (LAM) are run operationally in Europe. For example, the Deutscher Wetterdienst (DWD) Lokal-Modell (LM) has been implemented since 1997. LM was actually developed based on the DWD regional model DM (Deutschland Modell) with a new non-hydrostatic dynamical core (Doms and Schaettler, 1997). Under the Consortium of Small scale Modelling (COSMO) project, LM also has been operated in many other European countries like Switzerland, Italy, Poland and Russia. Yet another modelling system called High Resolution Limited Area Model (HIRLAM) (Unden et al., 2012) is used in several European countries (e.g., Denmark, Finland and Iceland). HIRLAM, which has an Eulerian version and a semi-Lagrangian version, has different configurations to meet the requirements of different countries and the non-hydrostatic version of HIRLAM has been presented by Room et al. (2006) in detail. A limited area model Aire Limitee Adaptation Dynamique Development Inter-National (ALADIN), which was developed by Meteo France, is also widely used in many countries like France, Algeria, Austria and Belgium. Its updated version, which has a non-hydrostatic core, Application of Research to Operations at Mesoscale (AROME) has been operated since 2008 (Seity et al., 2011).

In North America, Weather Research and Forecasting Non-hydrostatic Mesoscale Model (WRF-NMM) (Janjic et al., 2001; Janjic, 2003) has been operated by National Centres for Environmental Prediction (NCEP) since 2006 while in the National Centre for Atmospheric Research (NCAR), another version of WRF (WRF-ARW) (Skamarock et al., 2005) has been run for research and operations. A version of WRF-NMM with moving nests configuration was also developed and operated in NCEP since 2007 for operational hurricane forecasting. At Environment Canada, a Global Environmental Multiscale (GEM) model has been developed and operated since 1998 (Cote et al., 1998a and 1998b). It is worth noting that, although there is a non-hydrostatic option existing in GEM (Yeh et al., 2002), a hydrostatic configuration is still used for operational applications (Zaito et al., 2007).

In Asia, there are mainly two models developed for operational applications. JMA non-hydrostatic model (JMA-NHM) was used to replace the old hydrostatic spectral mesoscale model since 2004 (Zaito et al., 2007). JMA-NHM also has been operationally applied at
the Hong Kong Observatory (HKO) and blended with the radar nowcasts in Rainstorm Analysis and Prediction Integrated Data-processing System (RAPIDS) (Wong et al., 2006). In China, Global/Regional Assimilation Prediction System (GRAPES) (Chen et al., 2003) has been developed by Chinese Academy of Meteorological Sciences and operated at the National Meteorological Centre of China Meteorological Administration (NMC/CMA) since 2006.

In New Zealand, there are two numerical weather models used operationally. At NIWA, New Zealand Limited Area Model (NZLAM), which is a local implementation of the mesoscale configuration of the UK UM model system, has been operated at 12.0 km in horizontal resolution and 70 levels in vertical since 2013. A higher resolution version of NZLAM - New Zealand Convective Scale Model (NZCSM), which has 1.5 km grid point separation, is under testing at present. Weather forecasts in New Zealand are also provided by MetService using WRF-ARW at the highest resolution of 4.0 km (in 2013). Initial and boundary conditions are provided by data from UKMO NWP, European Centre for Medium-Range Weather Forecasts (ECMWF) and Global Forecast System (GFS). In contrast to the UM results obtained by NIWA, the WRF output is used as the guidance for all forecasting desks (severe weather, public, marine and aviation) in the New Zealand National Weather Service.

With more understanding about the atmospheric processes, especially the mechanisms of precipitation systems, the quality of the initial conditions becomes more and more important in NWP models. A number of previous studies showed that large forecast errors are usually generated by inaccurate initial conditions in the areas with clouds/precipitation (McNally, 2002). Small scale features and the temporal variability over a small period (e.g., several hours) might not have substantial effects on global NWP, which are usually run based on the mean statistics of the global scale (Ebert et al., 2007). However, significant errors, especially the misplacement of precipitation, can be found when comparing predictions with instantaneous observations (Bauer et al., 2011). Therefore, in order to provide high skill of precipitation forecasts over (very) short range, clouds/precipitation data are expected to be used to initialize NWP models. Several countries initialize their models with different types of clouds/precipitation data using different schemes. Table 1.1 gives a short summary of data assimilation schemes used operationally (Bauer et al., 2011).
The Japan Meteorological Agency (JMA) is probably the first operational centre that applied 4D-Var in their high resolution regional NWP model (the Mesoscale Model (MSM)) for assimilating radar precipitation analysis. At present, MSM and the associated radar data assimilation system are used to issue very short range warnings of high impact weather systems in Japan and the surrounding regions. The model has the capability of updating 8 times daily and the forecast is made up to 33 h ahead (Zaito et al., 2007; Honda et al., 2005). At Environment Canada (EC), Global Environment Multiscale (GEM) model is performed with data assimilation system 4 times a day. So far, observations from upper air aircraft, surface, satellite (winds and radiances) and GPS radio are assimilated using 4D-Var (global scale) and 3D-Var (regional-limited scale). The assimilation of North American radar data has been considered as one of the essential plans for further improving Canadian regional forecasts (Fillion et al., 2010). At Meteo France, a 1D+3D-Var technique has been employed to assimilate observations from National Radar Network. In the 1D+3D-Var technique, pseudo-observations of relative humidity (RH) are first retrieved from radar reflectivity through a 1-D Bayesian model. Then the RH fields are assimilated with other variables like temperature, winds using the 3D-Var system. Better description for short range precipitation forecasting can be found through the 1D+3D-Var method, especially for the lead times less than about 9 hours (Caumont et al., 2008; Bauer et al., 2011). At the UK MetOffice, rainfall data are assimilated into the UKV models using Latent Heat Nudging (LHN; see Jones and Macpherson (1997)). LHN has the ability of assimilating rainfall directly with less computational resources in comparison with variational methods, thus it is also widely used in other models like COSMO model for operational application or research. At NCEP/NCAR, 4D-Var system for assimilating radar reflectivity was developed recently (Wang et al., 2013a), but simplified methods are under development and the assimilation of radar observation is expected to combine with a hybrid ensemble analysis system in the future. At NOAA, the Rapid Refresh (RR) system is used as the continental-scale hourly updated assimilation/modelling operational system. A higher resolution (3.0 km) High-Resolution Rapid Refresh (HRRR), which only covers the area of the US, is updated hourly with 3 km radar reflectivity assimilation via a radar digital filter initialization technique (Benjamin et al., 2004, 2010; Bauer et al., 2011).

In New Zealand, currently there are no precipitating clouds/precipitation observations assimilated directly in operational models at high resolution. At New Zealand MetService, there are different types of synoptic observations, like 2 m temperature and 10 m winds,
assimilated through the nudging approach. Other data sources like AMDAR, buoys, satellite retrieved AMVS, METARS and ship observations are used to initialize the model. At NIWA, data assimilation is carried out at the NZLAM model using 3D-Var. Different types of data including observations from surface, radiosonde, aircraft, scatterometer, AIRS, IASI, ATOVS and GPS radio occultation are incorporated into the model every 3 hours. 4D-Var was tested by NIWA but it only gave marginal improvements at greatly increased computational cost thus it is not implemented operationally (personal communication with Dr. Phil Andrews at NIWA). Apparently, there is need for initializing NWP models with clouds/precipitation observations in next few years for New Zealand.

1.3 A short review of extrapolation based nowcasting

Nowcasting techniques for forecasting convective precipitation for the lead times less than several hours were developed in the 1960s. Depending on different types of precipitation systems, the premium period of nowcasting may be different. For example, for a tornado, due to its rapidly changing characteristics, the time scale for the nowcasting is usually less than a few minutes. While for a frontal precipitation, the time scale can last over many hours. Nowcasting of the location of convective storms is primarily based on the extrapolation based techniques with radar reflectivity. At first, two radar images taken at different times were simply correlated and an average motion vector was generated manually (Ligda, 1953) or by computer (Hilst and Russo, 1960). Those early stage techniques did not consider the predictability of precipitation in terms of different scale sizes. They assumed that the entire rain band moves along a single direction and there is no change in size or intensity. After that, Rinehart and Garvey (1978) first used multiple motion vectors, which are obtained by the cross-correlation method, instead of one single vector to represent the movement of precipitation. As a simple and efficient method, the precipitation nowcasting based on multiple motion vectors is still widely used today. Other than the extrapolation based on the entire radar images, the tracking of individual cells was also carried out based on radar reflectivity (Zittel, 1976). In contrast to the cross-correlation method, the main challenge for the individual cells tracking is to handle the splitting and merging of echoes. A lot of effort has been put into this problem since 1970s (e.g., Wolf et al., 1977; Dixon and Wiener, 1993). Thunderstorm Identification, Tracking, Analysis and Nowcasting (TITAN) system was developed based on individual tracking and it is adopted by the New Zealand MetService Ltd. operationally. A similar algorithm is
called Storm Cell Identification and Tracking (SCIT), which is a centroid-type tracker and
developed by Bjerkas and Forsyth (1979) and Witt and Johnson (1993). The Enhanced
TITAN method (ETITAN) (Han et al., 2009) was developed to combine the old TITAN
system and an area tracking method recently.

It is worth noting that, the optimal spatial resolution for extrapolated based nowcasting is a
power-law function of the forecast lead time (e.g., Bellon and Zawadzki, 1994). This
relationship was found to be nearly independent of different rain characteristics (Grecu and
Krajewski, 2000). Overall, as the time ahead of nowcasts increases, it is to be expected that
the large scale structures such as cyclones and fronts will persist and be predictable
whereas small scale features such as showers and small convective elements are likely to
disappear, split or merge. From this idea, a concept of dynamic and spatial scaling for
advection forecasting was discussed by Seed (2003). This approach is very useful in
operational applications and has been widely applied during the last several years.

In operations, the first automated nowcasting system, SHARP (Short-term Automatic
Radar Prediction) was operated at McGill Weather Radar Station in 1976 with the cross-
correlation technique (Austin and Bellon, 1974, 1982; Bellon and Austin, 1978). After that,
a system called “RainSat” (Bellon et al., 1980) was developed at McGill and implemented
in many places around the world (e.g., Nevada, 1990). At the US National Weather Service
(NWS), an interactive tool called the Weather Forecast Office Advanced System (WFO
Advanced) is used (Roberts, 1996). This system provides a set of algorithms for calculating
storm tracks, detecting different types of precipitation systems and estimating precipitation
accumulations. The TITAN system has evolved at the Research Applications Laboratory
(RAL) since the early 1980s. At present, the latest version of TITAN system is 5.0, which
was released in 2009. It has the capability of handling different types of data from radar,
satellite, lightning sensors and surface observations to numerical models. The TITAN
system is available for use under a free online license and has been installed at a number of
sites around the world including New Zealand. At the UKMO, the first nowcasting system
is called Forecasting Rain Optimized using New Techniques of Interactively Enhanced
Radar and Satellite data (FRONTIERS), which was implemented in the early 1980s
(Browning and Collier, 1989). More advanced systems, which couple extrapolation based
nowcasting with NWP models, like Nowcasting and Initialization for Modelling using
Regional Observation Data (NIMROD) (Golding, 1998) and Generating Advanced
Nowcasts for Deployment in Operational Land-Based Flood Forecasts (GANDOLF) (Pierce et al., 2000), were implemented after the FRONTIERS system. A state-of-the-art rainfall nowcasting system, Short Term Ensemble Prediction System (STEPS), has been developed by the UKMO in collaboration with the Bureau of Meteorology, Australian (BOM) recently with the concept of averaging ensembles of nowcasts (Bowler et al., 2006). This system is now operated at both BOM and UKMO. A new way to combine NWP models and extrapolation based nowcasting was proposed by Sokol and Zacharov (2012): the assimilation of nowcasting data was assumed to be able to prolong the effects of the initial conditions and therefore improve very short range precipitation further.

1.4 New Zealand precipitation distributions and the national precipitation observation network

New Zealand is a country surrounded by the Tasman Sea and South Pacific Ocean. It has complex climate from warm subtropical in the far north (e.g., Northland region) and cool temperature climate in the far south (e.g., Stewart Island). Over last several years, different approaches have been used to investigate the frequency and the intensity of (extreme) precipitation events in New Zealand. Griffiths (2007) gave the historical trends in rainfall using indices of extremity (IOE) from station data for the period from 1950 to 2004. The results showed that there was an increase of extreme precipitation in the west coast, and a decrease in the east over the selected period. A regional climate model has been used by Carey-Smith et al. (2010) and similar results were presented.

Figure 1.1 gives the mean annual rainfall (mm) for New Zealand, which is provided by National Institute of Water and Atmosphere Research (NIWA). In Northern New Zealand, which is a region with typical sub-tropic climate, south-west winds prevail for much of the year and bring moist air masses from the Tasman Sea. The maximum seasonal precipitation accumulation (up to about 180.0 mm month$^{-1}$) is usually obtained from June to August for four major urban areas (Kaitaia, Whangarei, Auckland and Tauranga) in this region. In the Central North Island, where includes three major cities - Hamilton, Taupo and Rotorua, less wind is usually observed than other parts of the North Island. Summer is usually warm and dry where winter is cool. However, compared to the Northern New Zealand, the difference between the rainfall accumulation in winter and summer in this area are not very significant. The southwest part of the North Island (New Plymouth,
Wanganui, Palmerston North and Wellington) is exposed to disturbed weather systems from the Tasman Sea and this leads to quite windy climate in this area. The annual precipitation accumulation in this region could go up to 1,200.0 mm. The Northern South Island is usually considered as the sunniest region of New Zealand as much of this region is sheltered by high country to the west. The maximum monthly precipitation observed in Nelson and Blenheim are less than 100 mm and 80 mm respectively, on average. The region that lies to the west of the Southern Alps is exposed to the weather systems from the Tasman Sea and largely due to the forced lifting provided by topography, the mean annual rainfall in this area is very high. Heavy rainfall, including very strong small scale cell, usually occurs in late summer and during the whole winter. The monthly precipitation accumulation in the area distributes more evenly compared to other places. For example, in Milford Sound, the precipitation accumulation in summer is even larger than that in winter. On average, the annual precipitation accumulation in the area can be as large as 3,000 mm, which makes the West Coast of the South Island as the wettest region in New Zealand. In contrast, mean rainfall in the Inland South Island (Queenstown, Alexandra and Manapouri) is low, which is largely caused by the shelter of the Southern Alps to the west. In Alexandra, the monthly observed rainfall was usually less than 40 mm and in Manapouri, where is considered as the wettest place in this region, the monthly precipitation was also less than 100 mm on average. The climate zone for the Eastern South Island is similar to the Inland South Island, which is largely dependent on the Southern Alps. In Christchurch, the annual mean precipitation is apparently lower than other main urban centres (e.g., Auckland and Wellington) of New Zealand. Based on previous statistics, the maximum monthly precipitation for this region usually occurs in July but the accumulation was less than 100.0 mm month$^{-1}$ on average. In Southern New Zealand, the weather is normally characterized by cool coastal breezes. The area has prevailing southwest winds but northwesterlies are more frequent in the region of Dunedin. Detailed information for the climate zone and the effects on precipitation distribution, including the description of the Figure 1.1, can be found from Mackintosh (2001).

New Zealand Meteorological Service Ltd. (MetService) currently operates a total of 8 Doppler weather radars which provide high resolution rainfall observations covering most regions of the country. In contrast to the short summary of the New Zealand National Radar Network given by Crouch (2003), nowadays MetService weather radars, which are
made by Vaisala, perform three dimensional scans every 7 minutes in Auckland, Bay of Plenty, Taranaki, Gisborne/Hawke’s Bay, Wellington, Westland, Canterbury and Invercargill with 7 elevations. The spatial resolution of the radars is range dependent from several hundred metres to a few kilometres. A two scan strategy is applied. The first scan covers an area out to a range of 480 kilometres with only radar reflectivity observed. The second scan covers an area out to a range of 240 kilometres, and is able to measure both velocity as well as radar reflectivity. The resolution in both space and time makes the radar network sufficient to characterize most types of precipitation from mesoscale to large scale, and also with some ability to represent small scale cells. A detailed evaluation of the errors inherent in the National Radar Network can be found from Shucksmith et al. (2011) and Sutherland-Stacey et al. (2011). Figure 1.2 gives a photo of the C-band radar located in Wellington, New Zealand which is operated by NZ MetService.

It is worthwhile to note that, in the thesis, radar data were postprocessed and quality controled by using two sets of open source libraries, one is called PyART (https://github.com/ARM-DOE/pyart) and another one is Wradlib (http://wradlib.bitbucket.org/). The following procedures were carried out before applied radar data to any experiments:

(1) The removal of non meteorological echoes: Clutter usually caused by the intersection of all or part of the radar beam from mountain, building or other similar earth surface features. Sometimes birds also contribute to the non-meteorological echoes. Geotis and Silver (1976) showed an efficient technique for removing the ground clutter by the use of Doppler velocity information. A more sophisticated approach ~ decision tree algorithm, was developed by Joss and Lee (1995). Besides, an innovative texture based algorithm was discussed by Gabella and Notapietro (2002). The texture based algorithm is easier to be implemented relative to the approaches which require the Doppler velocity and other information, and it has been adopted in Wradlib as the standard non-meteorological echoes removal program. A good discussion about the approaches for the clutter removal is shown in Gabella and Notapietro (2002).

(2) Attenuation correction: Since the radars operated by New Zealand MetService Ltd., are all in C-band, which means that the attenuation caused by heavy rainfall can be significant. There is a long history for the studies of the attenuation issues (e.g.,
Hitchfield and Bordan, 1954; Marzoung and Amayenc, 1994; Delrieu et al., 2000). Kraemer and Verworn (2008) showed one of the possible solutions to address this problem effectively, and the concept is to apply a specific attenuation K (based on Z-K relationship) repeatedly to different ranges. This method has been applied to the radar data quality control process in the thesis.

(3) Constant Altitude Plan Position Indicators (CAPPI): The vertical distribution of the observed reflectivity, earth curvature, beam elevation and different sampling heights contribute to the determination of the vertical profile of reflectivity and thus the Constant Altitude Plan Position Indicators (CAPPI). In Wradlib, both CAPPI and pseudo CAPPI can be produced. The difference between CAPPI and pseudo CAPPI is that the blind area out of the radar vertical range are not masked in pseudo CAPPI, instead, an interpolation algorithm (e.g., nearest-neighbour interpolation, Kriging or inverse distance weighting interpolation) is applied. It is worthwhile to mention that a simple vertical profile correction algorithm was applied to address the bright band issues in the thesis, after that CAPPI calculated at surface was used to produce all the rainfall maps.

(4) Z-R relationship: Marshall et al. (1974) attempted to set up the initial relationship between the observed reflectivity and rainfall rates. Overall, a simple expression of the relationship can be written as:

\[ Z = aR^b \]

Where Z is in mm$^6$m$^{-3}$ and R is in mm/h

A list of the recommended Z-R relationship (in the US) is given in Table 1.2 (see http://www.srh.noaa.gov/tlh/?n=research-zrpaper), while in this thesis, we simply applied the Marshall-Palmer relationship in all our studies. It is worthwhile to mention that, there may be significant uncertainties/errors involved in the selected Z-R relationship (e.g., Rinehart, 2004), and these errors can be propagated to the process of rainfall verification and other radar related activities, for example, the RK-nudging scheme applied in the thesis.

(5) Rain gauges calibration: As we mentioned above, there are significant uncertainties in the Z-R relationship, which means that there must be bias between the rainfall we got from
surface gauges and the one observed by radar. The bias can be significantly increased if we consider other factors, for example, the accuracy of radar estimates (e.g., Wilson and Brandes, 1979), the difference of the observation heights between radar and gauge, and the effects of winds. A practical way to reduce this bias is to apply the rain gauge calibration scheme to the radar.

Kriging interpolation may be the most widely used method for the rain gauges calibrations (Krajewski, 1987; Sun et al., 2000), while other approaches are also applied for different particular purposes. For example, Statistical objective analysis is developed by Pereira et al. (1998). Goudenhoofdt and Delobbe (2009) gives a good evaluation of radar-gauge calibration approaches over a long period. From their studies, even a simple method like mean field bias correction can reduce the bias of the radar estimates significantly. In the thesis, a Kriging method was applied. A general description of this method can be found from Goovaerts (1997) and Goudenhoofdt and Delobbe (2009).

Radar data quality control is a very critical issue for either the radar data assimilation or the radar data based verification. It is almost impossible to claim that we have “perfect” radar products at this stage, but by using the community weather radar packages including PyART and Wradlib, we hope we can at least avoid/reduce some of the errors and work with the radar rainfall maps with higher quality relative to the native ones.

Besides radar, meteorological satellites are also used by NIWA and MetService for providing cloud information over the Tasman Sea. Considering the development of precipitation is usually fast, the Geostationary Operational Environmental Satellite (GOES) operated by National Oceanic and Atmospheric Administration (NOAA), and the Multifunctional Transport Satellite (MTSAT) launched by Japan Meteorological Agency (JMA) are only two series of satellites can provide relatively high temporal resolution observations (about 30 min) for New Zealand (MTSAT has better view of New Zealand compared to GOES, but the data are not available in our university). It is worth noting that, precipitation cannot be measured by satellite directly, usually it is determined by related information like cloud location, thickness and height. The indirect relationship between the variables that satellite measures and precipitation usually leads to significant errors, especially during the night time when the visible channel is not available.
Chapter 1. Introduction

It is worthwhile to mention the errors which may inherent in the satellite remote sensing data. The errors can usually be divided into three categories:

(1) In the fringe area, the image may be darker compared to the central area. This is called vignetting, which can be expressed by \( \cos^2 \theta \), where \( \theta \) is the angle between the ray and the optical axis.

(2) The errors caused by the solar radiation and topography

(3) The absorption and scattering of the solar radiation due to various atmospheric effects.

The detailed descriptions of the errors and the related correction methods can be found in http://wtlab.iis.u-tokyo.ac.jp/~wataru/lecture/rsgis/index.htm. In this thesis, the gridded GOES data at Level 1B were used.

Other than remote sensing based techniques, traditional rainfall measurement tools like rain gauges still play a very important role in precipitation observations in New Zealand. In contrast to radar and satellite, there is a significant drawback that the spatial resolution of rain gauges distribution is relatively sparse. However, rain gauge provides the most direct way to measure the rainfall accumulation over a certain period. In New Zealand, the data measured by rain gauge are used as a “truth” field to adjust other precipitation observations like radar and satellite (e.g., Shucksmith, 2012).

1.5 Spatial resolution dependant objective skill scores

Skill scores are usually used to evaluate the quality of the precipitation forecasts in an objective way. It is important to note that forecast skill scores like Critical Success Index (CSI), Equitable Threat Score (ETS) and False Alarm Ratio (FAR) are very resolution dependent. For example, Figure 1.3 shows a simulated cell (left) produced by a model and the corresponding observation (right). If we carried out the verification at the resolution of 1.0 km, we can easily find that there are three grid points (a, b and c) fitting to each other, while for points d, e and f, the simulation overestimates the rainfall and for point g, rainfall is underestimated. This indicates that the CSI at 1.0 km should be \( \frac{3}{3+3+1} = 0.4286 \). If we reduced the horizontal verification resolution to 1.5 km (the verification points are indicated by orange dots), we have two points (g and i) fitting to each other. The simulation underestimates the rainfall at one point (j) and overestimates it at another point k, therefore
the CSI for 1.5 km increases from 0.4286 to \( \frac{2}{2+1+1} = 0.5 \). If we carried out the verification at 4 km (indicated by yellow dot), it is apparent that we can get the CSI of 1.0 (perfect score).

Therefore, it is clear that we are always easily able to achieve higher statistical scores by decreasing the verification resolution. Indeed the CSI (or ETS) for the prediction that it is raining somewhere on the global is always 1.0. Conversely, the CSI score for any prediction of what falls in one rain gauge is likely to be very small. This issue also applies to the verification thresholds used, as intense precipitation is usually presented at a much smaller scale. It makes the simple comparison with the objective skill to be pointless if we do not take the verification resolution (and threshold) into account.

Overall, what we discussed above is the well known “double error counting” problem when we use the traditional grid by grid verification skill scores to exam the mesoscale features in high resolution models (Cintineo et al., 2014). Those scores are easily penalized when small features are temporally or spatially displaced by a small amount, even though the structure of the forecast feature itself is more realistic (e.g., Cintineo et al., 2014; Roberts and Lean, 2008). More complicated scores, such as Fractional Skill Score (FSS) (Mittermaier and Roberts, 2010), can be used to address this issue in a more appropriate way. For example, FSS scores used in Chapter 5-8 has the capability of comparing rainfall forecasts and radar data by using fractional coverage over different sized areas, which gives more reasonable evaluations for intense and discontinuous rainfall system. It is worth mentioning that, the objective of this thesis is to apply high resolution datasets to assist in the assimilation of rainfall, thus we have kept the resolution of most of the verification reported here at the highest level except the statistics of FSS.

1.6 Challenges and opportunities of New Zealand precipitation forecasts

Currently, operational precipitation forecasting over New Zealand are provided by MetService for 3 days ahead at a relatively high resolution (8.0 km) and 5 days forecasts at low resolution (16.0 or 60.0 km depending on the global model used.). All forecasts provided by MetService are provided by human forecasters with the guidance from the Weather Research and Forecasting (WRF) Model, which is not a fully cycling system. NIWA also provides nature hazard forecasts (including precipitation) while the UK
Unified Model (UM) is used at the resolution of about 10 km (the newest version of the UM adopted in NIWA has a resolution of 1.5 km). So far, there are no precipitation observations being assimilated into models directly in New Zealand. However, it is well known that forecasting is usually particularly sensitive to the regions of clouds and precipitation, where are the active regions of the atmosphere (Bauer et al., 2011). However, unlike the simulation of clear-sky variables like temperature from in-situ observation, which are usually controlled by relatively linear processes, clouds/precipitation data are difficult to be modelled adequate in most configurations and this makes the assimilation of clouds and precipitation essential for satisfying the growing need for accurate forecasts of severe weather.

However, there are also a number of issues affecting the skill of initializing models with high resolution observations. Bauer et al. (2011) summarized the major issues:

1. In data assimilation system, the sensitivity of forecast skill to the accurate initial conditions is still not well known. Moreover, the assumption of a linearized observation operator and the non-Gaussian error characteristics can lead to significant errors during the assimilation processes,

2. Besides the errors existing in the data assimilation system, the parameterization of clouds and precipitation is still very crude, which means that the observed information can be lost quickly during the early time steps. But it is worth noting that, poor balance in the analysis and the limited predictability of convective activities may also contribute to the problem of the quick loss of observed features.

It is also worthwhile to mention the limited computational resources in New Zealand. Although progress has been made in the technology of large computing facilities over last several decades, it is still unreasonable to expect to be able to use a grid spacing of $O(100 \text{ m})$ in operational applications. At present the highest resolution run by the NZ MetService model is 4.0 km, and at such grid spacing, traditional convective parameterization is usually not required, but convection cannot be fully resolved. The facilities required to run models at the resolution with the capability to resolve convection will probably not be around for next several years, so the resolution related issues would continue. In addition, limited computing facilities also limit the ability to assimilate high resolution data into NWP models. For example, VAR schemes in general, and 4D-Var in particular, requires computational resources beyond the capability of most university groups and indeed some
national forecasting centres of countries like New Zealand. In NOAA or UK Met Office, the performance of VAR is also largely affected by the availability of large computational resources. For example, the calculations of 4D-Var are usually performed at a coarser grid than that which the model is actually run, which can be much coarser than the radar observation, due to the expensive computational demand (Sokol and Zacharov, 2012). Overall, in the next many years, limited computing facilities will remain as one of the major issues for improving precipitation forecasting in New Zealand.

Although there have been significant improvements made in precipitation forecasting in New Zealand over last several decades, the combination of clouds/precipitation observations and other in-situ data sources with high resolution NWP model is expected to be an opportunity to improve the forecasting further. Some of the issues presented above have been investigated in this thesis.

1.7 Research objectives
The objective of this thesis is improving (very) short range precipitation forecasting in New Zealand. In order to achieve that, both extrapolation based technique and NWP model are used:

(1) For extending the availability of high resolution rainfall information out of the range of National Radar Network, a VIS/IR images based technique called “RainSat” (Bellon et al., 1980) is to be implemented for New Zealand. The errors inherent in the “RainSat” technique should also be investigated.

(2) For improving extrapolation based nowcasting, the “RainSat” technique can be used as supplemental information when a rain band cannot be delineated completely by radar.

(3) WRF is used to provide precipitation forecasts beyond about 2-3 hours. In order to incorporate clouds and precipitation observations into the model and avoid expensive computing resources, a nudging based technique is developed.

(4) Both satellite and radar data are planned to be assimilated into WRF and the results are expected to be helpful to investigate the possible future operational implementation of
clouds/precipitation assimilation in New Zealand.

Finally, we attempt to combine extrapolated data and NWP model results: precipitation forecasts produced by the extrapolation based technique are planned to be assimilated into WRF at the lead time of 1 hour to test if this prolonged improved initial condition can actually help the forecasting for subsequent hours.

1.8 Organization of the thesis

After the general introduction in Chapter 1, Chapter 2 presents the implementation of the “RainSat” technique in New Zealand. The associated errors inherent in “RainSat” are investigated in next Chapter (Chapter 3). This is followed by the description of the approach of applying merged radar and satellite data for improving precipitation nowcasting (Chapter 4). The implementation of the precipitation nudging assimilation using a reverse Kessler warm rain scheme is presented in Chapter 5. Sensitivity studies of the implementation of the new nudging scheme with different model microphysics schemes are then presented in Chapter 6. The results obtained from the experiments with radar and satellite data assimilation are presented in Chapter 7 and is followed by the descriptions of the assimilation experiments with radar/satellite extrapolating nowcasting data. Chapter 9 presents the summaries and conclusions. Parts of Chapter 4, 5, 7 and 8 have been presented or published in Zhang et al. (2014), Zhang et al. (2012), Zhang and Austin (2013) and Austin et al. (2012). Organizations of the thesis and the motivations for each chapter can be found from Figure 1.
Chapter 2. Implementing the “RainSat” technique for improving precipitation observations in New Zealand

2.1 Abstract
Most high impact weather systems affecting New Zealand initiate and develop over the Tasman Sea out of the range of National Radar Network. This makes the use of satellite data essential in New Zealand or other similar island countries. In this chapter, we employed a technique called “RainSat” to delineate the rainfall probability map over the sea, which greatly extends the availability of precipitation information compared to that obtained from the traditional radar alone observation network. The “RainSat” technique is also used to provide nowcasts in New Zealand based on the cross-correlation extrapolation technique. Verification against the associated radar data showed that moderate improvements in rainfall pattern estimates could be found using the “RainSat” based nowcasting compared to the traditional techniques made using radar data alone.

2.2 Introduction
New Zealand is an island country located in the south-western Pacific Ocean. Geographically, New Zealand is situated about 1,500 km east of Australia and 1,000 km south of other Pacific island countries like Fiji and Tonga. Two main islands (the North Island and the South Island separated by Cook Strait) and a number of smaller islands constitute New Zealand. Figure 2.1 gives the location of New Zealand and its surrounding nations. The National Radar Network is operated by New Zealand Meteorological Service Ltd., which consists of eight Doppler radars at present. It is capable of providing high resolution precipitation and Doppler winds measurements out to a maximum range of 200 km from the coast (see Section 1.4). The area out of radar range, for example, over the Tasman Sea, where most high impact weather systems initiate and develop, is not covered by any direct precipitation or winds measurements so far. One thought is deploying ships with some precipitation measurement instruments over the Tasman Sea, however this is extremely costly and the coverage area of the observations based on each ship would be modest so that multiple ships would be required. Such systems deployed off shore elsewhere in the world have mostly been abandoned. Figure 2.2 gives an example of the typical development of a frontal precipitation event affecting the North Island of New Zealand. From the local time of 1300 (New Zealand Time, NZT) on 04 Nov 2013, a low
pressure system developed from the bottom of the Tasman Sea, and the centre gradually moved northward and started affecting the North Island from 0700 NZT on 05 November, which led to significant rainfall in the west coast of the North Island. This suggests that, to improve precipitation forecasting further in New Zealand, it would desirable to obtain precipitation and winds estimates over the Tasman Sea.

In order to obtain high resolution precipitation information over the Tasman Sea, satellite observations are required, as satellite is the only instrument that has the capability of providing monitoring of high impact weather globally with relatively high temporal and spatial resolutions. However, in contrast to other instruments like rain gauges, precipitation usually cannot be directly observed by satellite. Satellite retrieved rainfall is usually retrieved from the visible (VIS), infrared (IR) or microwave sensors installed, or the satellite-borne radar like TRMM Precipitation Radar (Note that TRMM has been gradually replaced by Global Precipitation Measurement (GPM) since 2014.). Significant uncertainties exist in terms of the response of the different sensors and retrieval algorithms to the various characteristics of different rainfall processes. In New Zealand, or other island countries in the south hemisphere, due to the greater lack of ground observations compared to the continental countries in the north hemisphere, the validation of the satellite based rainfall estimates becomes an more significant issue.. Other than using satellite for monitoring purpose, considering air masses are usually advected from beyond the radar range, it is also to be hoped that the use of satellite data in NWP model can improve QPF in New Zealand. It is apparent that the use of satellite might not be providing very accurate precipitation products compared to radar or rain gauges, but it may well be better to have rough estimates of rainfall distributions and cloud tracks over the Tasman Sea than no information at all. In this chapter, the issues of the implementation of the “RainSat” technique over the Tasman Sea and New Zealand are discussed.

2.3 Satellite precipitation measurements
There are a number of satellites used for measuring precipitation on a global scale. Most of them can be categorized as geostationary or polar-orbiting. A geostationary orbit is a circular orbit around 35,000.0 kilometres above the Earth’s equator and the orbital period of the satellite is equal to the Earth’s rotational period. In contrast, a polar-orbiting satellite has an orbit that passes above both poles of the Earth. According to The Global Observing
System (WMO, 2005), polar orbiting satellite has been included into the category of Low Earth Orbiting satellites (LEO). Kidd and Huffman (2011) summarized the most commonly used satellites for precipitation measurements before GPM (listed in Table 2.1).

For geostationary (GEO) observation systems, each satellite has the capability of monitoring about 1/3 of the Earth’s surface in principal but significant errors exist in areas with large scan angles (near the extremities of the imagery), at least five operational satellites are usually required to provide a full global coverage (e.g., 70°N – 70°S). Widely used GEO satellites include MSG, GOES, Fengyun (operated by CMA) and MTSAT (operated by JMA). In contrast to GEO, LEO observing system usually only provides up to two images daily for a given location away from the pole. Besides IR and VIS sensors, passive microwave (PMW) sensor, which measures precipitation more directly, is usually installed in LEO system. NOAA satellites, MetOp series satellites and TRMM (or GPM later) are three main LEO satellites useful in weather forecasting now. It is evident that GEO satellites are capable of providing information in high temporal resolution, but its IR/VIS channels are indirectly sensitive to precipitation. LEO satellites can provide more direct precipitation measurements particularly with passive microwave sensors, whilst the temporal resolution (twice daily) is generally not enough for monitoring mesoscale convective systems.

In order to estimate precipitation from GEO satellites, a number of VIS/IR methods were developed. Most of them are based on the assumptions that (1) thicker clouds are usually corresponding to very bright shown up in visible image and they have more possibility of raining; (2) cold clouds from infrared image have higher cloud tops and may be more likely to rain compared to clouds with a lower and warmer cloud top. An early approach for precipitation retrieval using visible channel alone was shown by Follansbee and Oliver (1975), although the relationship between cloud brightness and precipitation is relatively poor (Kidd and Huffman, 2011). In contrast to visible alone approaches, IR alone methods have been widely used during the last several decades but tend to overestimate rain areas from areas of thin cirrus clouds. Early operational IR based methods include the Global Precipitation Index (GPI) (Arkin and Meisner, 1987), the Convective/Stratiform (CST) technique (Adler and Negri, 1988), the Autoestimator (Vicente et al., 1998) and the recent Hydroestimator that is developed by Scofield and Kuligowski (2003). Dual-channel
techniques like the one developed by Lovejoy and Austin (1979) and Bellon et al. (1980) add more constraints to the delineated precipitation. By introducing the cloud thickness information (from the visible channel), the cloud top information (from the IR channel) and using the precipitation from the radar network as "ground truth", the precipitation area can, it may be hoped, be estimated more accurately than the single channel methods (King et al., 1989, 1995).

Passive microwave remote sensing methods have the advantage that the precipitation in a cloud actually emits radiation in the microwave spectrum, and most clouds are transparent to microwaves. Most PMV based techniques were developed using multi-channel methods with empirical or physically derived relationship to distinguish the signals from cloud water, rain and snow. Kidd et al. (1998) summarized the advantages and disadvantages of the PMW based precipitation estimation method. For our particular project, the main difficulty with the PMW based observations is that they are only available twice daily and their spatial resolution is usually relatively low (> 10 km and often as much as 50 km) due to the relatively long wavelength of the microwave channels compared with visible and IR light.

Active microwave, which usually means radar technology at the spaceborne satellite, provides the most direct satellite precipitation observation. One good example is Tropical Rainfall Measuring Mission (TRMM) Precipitation Radar (PR). TRMM PR has operated since 1997. Like all ground based radar systems, the PR system relies on backscattering from rain droplets, although the relationship between rain rate and the radiation of droplet backscattering may still have significant errors and because a low orbit is required to give adequate spatial resolution, the satellite is not in Geostationary orbit so that the temporal resolution is poor. Moreover, TRMM PR is only available in tropics and thus New Zealand is out of its footprint. TRMM PR has been extensively described and reviewed by Stephens and Kummerow (2007). The CloudSat satellite, which was launched in 2006, is the first W-band cloud radar that is able to identify cloud properties along the nadir track. However, due to the relatively low temporal resolution (see Table 2.1), CloudSat has not been widely applied to (very) short range precipitation forecasting so far. It is worthwhile to mention that an international satellite mission, Global Precipitation Measurement (GPM), was launched by NASA and JAXA (Japan Aerospace Exploration Agency) on Feb 27, 2014. GPM data can be categorized into two groups, near real-time data are available after a few
hours of observation but it is considered to be less accurate than the production data, which are only available after several days, or in some cases, several months after the satellite observations are taken.

In this chapter, a VIS/IR blended approach – “RainSat” is applied in New Zealand for delineating high resolution precipitation estimates. The reasons of selecting the “RainSat” technique include: (1) it can be easily implemented for operational usage at next step; (2) the temporal and spatial resolution of the “RainSat” retrieved precipitation are relatively high (temporal resolution: about 30 min; spatial resolution: about 5 km on average), which makes the “RainSat” technique well suited for mesoscale precipitation monitoring and forecasting; (3) In contrast to IR alone technique, VIS/IR blended approach usually can provide the highest correlation compared to the ground-based observations due to not assuming that high cirrus clouds are likely to be precipitating.

In this thesis, two platforms are used: GOES-11 (or GOES-West) was positioned at 135 degrees West longitude, and monitored North America and the Pacific Ocean basin. Together they provided weather observations that covered over 50 percent of the Earth's surface (http://www.nesdis.noaa.gov/). Considering that the GOES-11 was nearly out of fuel, and those unavoidable radiation damage and other aging effects since its launching, GOES-15 replaced GOES-11 as the operational GOES-West satellite from December 6, 2011. Since the selected period for our cases ranged between November 2011 and January 2012, both GOES-11 and GOES-15 satellites data were used in the thesis. Detailed information about these two platforms can be found from CLASS and NESDIS.

It is worthwhile to mention that, due to the transition of the platforms, inevitably we cannot get the same quality of the observations. For example, GOES-15 imager visible channel is centered at 0.63 µm while for GOES-11 it is 0.65 µm, therefore for GOES-15, the visible imagery may appear a bit “darker” in clear-regions. In addition, from GOES-11 to GOES-15, the resolution of IR channels has been increased. However, for the concept used in “RainSat”, the bifrequency distribution does not depend on any historical statistics, and before applying the algorithm, thinning has been applied to the dataset. Therefore, we assume that the impact of the GOES-West upgrading on producing the “RainSat” based rainfall estimates could be ignored. See (http://www.nesdis.noaa.gov/news_archives/goes_11_15.html).
2.4 The implementation of the “RainSat” technique in New Zealand

The “RainSat” technique, which was first developed by Lovejoy and Austin (1979) and Bellon et al. (1980), is capable of estimating the probability of rain from satellite data. This probability is determined by using a pattern recognition technique that compares IR/VIS radiances at a point with co-located ground observed rainfall (e.g., radar derived rainfall accumulations). The technique is started by the remapping of satellite data, which includes producing the equivalent map projections for both satellite images and radar data and correcting the visible data for varying sun angle. In this chapter, VIS and IR images and the corresponding radar data were remapped on a 401 × 401 array with a grid resolution of 5 km, which gives an extensive area beyond the range of New Zealand National Radar Network. The remapping process was carried out using a simple nearest neighbour interpolation method. However, it is worth noting that the resolutions for raw radar and satellite data are different in different locations (the resolution of observation is determined by various factors, for example, the distance between radar station and the target grid-point for analysing, projection approaches, satellite scanning angles etc.), and different interpolation methods may cause slightly different results. Figure 2.3 shows the scheme for estimating precipitation probability using the “RainSat” technique (Bellon et al., 1980).

After the remapping of satellite and radar data, the probability of rain distributions as a function of IR and VIS radiances (Equation. 2.1) is calculated from the combination of two bivariate frequency distributions obtained from VIS, IR and the corresponding radar imagery. During the bivariate frequency distributions generating processes, \( R_r \) and \( R_{nr} \) represent the radar points with rain and non-rain, respectively. The set of IR and VIS radiances at the same point of \( R_r \) or \( R_{nr} \) becomes the subscripts of a contingency matrix in Equation 2.1:

\[
P_{rx} = \frac{R_r(\text{IR},\text{V})}{R_r(\text{IR},\text{V}) + R_{nr}(\text{IR},\text{V})} \tag{2.1}
\]

Where \( R_r(\text{IR},\text{V}) \) and \( R_{nr}(\text{IR},\text{V}) \) represent the number of occurrences of rain and non-rain, respectively with the associated IR and VIS radiances. At the last step, the empirical relationship obtained within radar range is extended to other places (e.g., the regions out of the range of radar). Thus, the probability of rainfall can be delineated over the entire domain of interest. Detailed descriptions of the “RainSat” technique can be found from
In this chapter, the extrapolation of the “RainSat” retrieved precipitation was also carried out based on the extrapolation of the associated VIS/IR radiances. We did not extrapolate the retrieved probability directly, because the difference between two adjacent blocks (areas) from the probability map are usually very small, which makes the comparisons of the calculated correlation coefficients between different blocks difficult. Figure 2.4 gives a sketch of how the probability map has been temporally extrapolated in this chapter.

First, observed VIS and IR imageries are coupled with the associated radar data to produce the “observed” probability maps at (T-1) and (T). Second, the optimal probability threshold for retrieved precipitation (\(P_0\)) is determined by reducing the rainfall area in the probability map to match the associated area of radar echoes. In this chapter, this process is completed automatically by computer: the rainfall area is reduced by increasing the probability from the minimum 10% to the maximum 100%. The accuracy of the “RainSat” retrieved results (represented by \(S\)) at a certain probability is determined by Equation 2.2, which is a weighting function of Critical Success Index (CSI) and False Alarm Ratio (FAR):

\[
S = a \times CSI + b \times (1 - FAR)
\]  

(2.2)

It is worthwhile to mention that the selection of the optimal method for determining the probability threshold is still an open question, here we just applied a crude approximation. From the definition of CSI, it represents how well does the forecast “yes” events correspond to the observed “yes” events. It is sensitive to hits, while penalizes both misses and false alarms (see [http://www.cawcr.gov.au/projects/verification/](http://www.cawcr.gov.au/projects/verification/) for more details). According to our experiments, the “RainSat” technology most likely would overestimate rainfall area. In order to address this problem, we introduced the term of (1-FAR) in our weighting function. If rainfall is overestimated, FAR increases and then (1-FAR) becomes smaller. How to balance CSI and (1-FAR) is controlled by \(a\) and \(b\) in the thesis. Here \(a\) and \(b\) were both set to 0.5 in this chapter. Figure 2.5 (right-bottom) gives an example of the native rainfall delineation from “RainSat” (with all calculated probabilities) obtained at 0000 UTC 30 Dec 2011. The associated \(S\) scores against radar data in terms of different probabilities are given in Figure 2.6. It is clear that, with the selected probability threshold increased, \(S\) score increased as well and the peak of \(S\) was achieved when the probability
set to 60%, then the score decreased rapidly. This indicates that by implementing Equation 2.2, the range of optimal probability threshold $P_0$ for this case should be set between 60% and 100%. It is worthwhile to mention that the optimal probability threshold is largely determined by the threshold set for the radar data. In this chapter, the threshold for radar reflectivity was set to 15.0 dBZ.

After the optimal probability threshold $P_0$ was determined, the VIS and IR radiances from satellite imagery at the non-rain grid points are removed. Then, the adjusted VIS and IR (without grid points that are non-rain) at (T-1) and (T) are used to produce the extrapolated VIS/IR imageries at subsequent times using the cross-correlation method (noted as $VIS'$ and $IR'$ in Figure 2.4). The observed radar reflectivity at (T-1) and (T) are also used to provide radar based extrapolations for the next 3 hours (T+1, T+2 and T+3) (noted as $RADAR'$ in Figure 2.4). As the final step, extrapolated satellite images ($VIS'$ and $IR'$) are coupled with the corresponding extrapolated radar imagery ($RADAR'$) to produce the extrapolated “RainSat” derived rainfall probability map ($RAINSAT'$). During the practical operation, it was found desirable to remove isolated rain points (determined by the occurrences of rain points N within a $5 \times 5$ block: if N was less than 10, the block was eliminated from the subsequent calculations) during the extrapolation process.

2.5 “RainSat” based nowcasting experiments in New Zealand

This section evaluates of the "RainSat" probability based nowcasting technique with a selection of 13 relatively heavy rain cases which occurred during the summer of 2011/2012 (between Nov 2011 and Jan 2012) in New Zealand. All available radars operated by MetService were employed to generate the “RainSat” analysis. The 24 h rainfall accumulations for the selected cases observed by NZ National Institute of Water and Atmosphere Research (NIWA) and NZ MetService Ltd. are presented in Table 2.2. Two satellite imageries used for generating extrapolation were obtained at UTC 2252 and UTC 2352 with the interval of 1 hour for each case. The radar reflectivity map observed at the same time was used as the “ground truth”. The 1-3 hours nowcasts were evaluated by comparing the extrapolated estimates with the observed radar data at the forecast times and locations.

Figure 2.7 gives the CSI and FAR scores combined over all the selected cases. It is evident
that the “RainSat” technique was capable of providing 1-2 h nowcasts with relatively higher scores but the forecast skill decreased dramatically after that. On average, we find that the optimal retrieved probability lie between 30% - 40% (for 1 h nowcasts), which was in good agreement with the calculated optimal probability threshold (not shown). It is worthwhile to note that FAR scores also decreased (similar to CSI) as the lead hours increased. This is mainly resulted from the “RainSat” technique itself and also from the cross-correlation technique: the size of bivariate frequency distributions table for the “RainSat” technique decreased, which made the area of retrieved rainfall decreased as well. In this chapter, unskilled scores were calculated based on the radar based nowcasting at 6 hours. It is worth noting that the persistence and climatology may be referred as the best practice of “unskilled” forecasts (WWRP/WGNE, 2009). However, due to the limitation of the available data for our studies, neither approach was adopted. From the maximum cross correlation between radar echoes as a function of time for different types of weather systems (Wilson, 1966; 1998), we can tell that the cross-correlation based extrapolation has very limited skill for most weather patterns after 2 hours, although the effective period of extrapolation may be longer for some more organized systems (e.g., cyclones). Therefore, we simply adopted the skill of 6 hours nowcasts as our unskilled reference throughout the thesis.

Comparing the combined CSI and FAR for the “RainSat” analysis to that of radar within the radar range (Figure 2.8), we find that, for 1 h nowcasts, the extrapolation of the “RainSat” retrieved probability (with the optimal probability threshold of 30%) was able to yield higher CSI scores (“RainSat”: 0.37 vs radar: 0.3) and similar corresponding FAR scores. This indicates that, rather than just extending the availability of rainfall information out of radar range, “RainSat” may actually improve the nowcasting within radar range. The reason is easy to understand: due to the limitation of radar detectable range, sometimes radar cannot fully capture a rain band due to being partly out of range. The limited and incomplete rainfall information may result underestimates of the actual rainfall area and consequently generate less accurate motion vectors at subsequent hours. The uncertainties and errors caused by the use of incomplete radar echoes in nowcasting are discussed in Chapter 4.

From Figure 2.9, which is an example of one hour nowcast made by radar reflectivity and the “RainSat” analysis (obtained at 0000 UTC 01 November 2013), we can clearly see how
the use of the “RainSat” probability map could be beneficial to the support of offshore businesses in the area that is not covered by radars. By comparing the “RainSat” probability extrapolation to the radar alone extrapolation (dBZ > 15.0), we find that they are in general good agreement with each other within the radar range. Slightly positive effects were even introduced by using satellite imageries. For example, the extrapolated probability map presented the moderate possibility (over 50%) of rainfall in the middle of the North Island, which was more realistic compared to the radar alone extrapolation. We also found that rainfall estimated by the “RainSat” technique near the bottom of the South Island has significant probability (60% on average), which was not observed by the radar. We may explain it as the blocking effects of the radar detection in the mountain and hilly regions, but it also could be caused by the cloud and rainfall processes occurring there may well be different from those occurring in more northerly. As the main purpose of this chapter, the biggest contribution of cloud analysis using satellite imagery is that it is able to extend the availability of rainfall information and the associated nowcasting ability to the Tasman Sea. From the “RainSat” probability map in this case, we can determine that the precipitation initiated over the Tasman Sea might continually affect New Zealand for next several hours with the occurrence of westerly winds, which was verified by visual evaluations of the subsequent radar reflectivity maps (figures not shown).

2.6 Conclusions

This chapter describes the implementation of the "RainSat" technique over the Tasman Sea and New Zealand, and the use of the “RainSat” derived rainfall probability maps for the purpose of nowcasting. 13 relatively heavy rainfall cases occurred from November 2011 to January 2012 in New Zealand have been used to investigate the “RainSat” based nowcasting scheme. Because there are no direct observations over the Tasman Sea, the verifications were carried out within the radar range. The skill scores showed that the extrapolation of the “RainSat” probability map was able to provide relatively reliable 1-2 hours nowcasts for precipitation pattern. While after about 2 hours, the size of bivariate frequency distributions table decreased rapidly and the “RainSat” retrieved rainfall area became very small and yielded poor CSI and FAR scores. It is worthwhile to mention that the statistical scores may show significant variation in different seasons in view of the large seasonal differences in predominant cloud types and rainfall processes. (King et al., 1989).
From the discussions above, we can see the importance of the implementation of relatively high-resolution satellite retrieved precipitation analysis. Satellite data are able to provide information everywhere and this makes its use essential in areas that are not covered by radar. In New Zealand, the implementing of the “RainSat” technique may help to improve our understanding in precipitation system over the Tasman Sea. The work at next step involves the assimilation of the “RainSat” retrieved rain rates for improving the initial conditions of NWP. The extrapolated “RainSat” rain rates (“RainSat” based nowcasting) are also expected to be assimilated into NWP models in order to prolong the effects of initial precipitation fields and thus the model precipitation-affected variables for a longer time.
Chapter 3. Errors inherent in the “RainSat” technique

3.1 Abstract
The "RainSat" technique, which attempts to delineate a rainfall probability map using information from both the infrared and visible channels of geostationary satellite imagery, is extended to attempt to provide precipitation estimates and precipitation nowcasting over the Tasman Sea, beyond the range of New Zealand National Radar Network. The estimated rain rates based on the “RainSat” technique are expected to be used to initialize NWP models in New Zealand as the next logical step. However, the errors inherent in the “RainSat” technique have not been investigated quantitatively yet in New Zealand and it is essential to understand the source of the errors of the technique before the implementation of a “RainSat” type rainfall pattern based data assimilation scheme. In this chapter, four major errors, which may affect the skill of the “RainSat” technique, have been discussed: (1) The regression issues (that is the use of an empirical VIS/IR to rainfall conversion algorithm derived for one location and time at a different location or time); (2) Satellite data sampling errors; (3) The uncertainties when determining the “RainSat” analysis equivalent precipitation height and (4) the errors in estimating the precipitation intensity based on the “RainSat” delineated probability map. These errors and uncertainties are investigated and the skill of the “RainSat” analysis was verified against different observations using different objective skill scores. The results are expected to be informative to the use of the “RainSat” based precipitation analysis in the future, including those involving data assimilation in numerical weather prediction.

3.2 Introduction
The characteristics of different types of clouds and synoptic systems will be likely to result in differing distributions of satellite observed VIS/IR radiances. Besides, the same rainfall process may show distributions that vary significantly in space and time. For example, cumuliform clouds often exhibit a lumpy texture caused by the shadows on the irregularly shaped cloud tops (Conway, 1997). Thus, the bi-frequency table of the “RainSat” technique for cumuliform clouds may be large, more dispersed and includes more elements. In contrast, stratiform clouds are usually flat and more organized, which may yield more organized and less dispersed bi-frequency distributions. Moreover, there may be different types of clouds/precipitation systems existing in the same area of interest and significant
errors can be introduced by inappropriately extending the bi-frequency distribution for one type of cloud/precipitation to others. The errors caused by the uncertainties in the bi-frequency table labelled as the “regression issues”.

Another error may affect the size and distributions of the VIS/IR bi-frequency table. For VIS/IR radiances from satellite are usually capable of providing useful information about cloud characteristics. However, high resolution data also may yield a larger range of radiances with more details. Considering the “regression issue”, those details would bring negative impacts if we want to extend the usage of bi-frequency table. Moreover, considering the predictability of rainfall systems, relatively large and stable precipitation systems (that can be represented well by relatively low resolution data) usually can be predicted better than smaller features (Seed, 2003). Consequently, the selection of the resolution of satellite data could affect both the “RainSat” delineated precipitation and the “RainSat” based nowcasting.

In addition, for incorporating the “RainSat” retrieved precipitation into the model, the effective height of the analysis must be determined as accurately as possible. Naturally, since we are delineating precipitation, one would expect the rainfall to reach the ground. However, the models need to know the heights at which the bulk of the latent heat is released. The “RainSat” based precipitation estimates use satellite images from cloud tops in the absence of cloud information at other levels so the estimation of the effective height of precipitation generation is problematical unlike the situation with radar data. This error is not avoidable, and has to be investigated in order to determine the potential risks in assimilating the “RainSat” based rain rates into the NWP models at erroneous heights.

The “RainSat” technique is better at delineating precipitation area and location than intensity. However, in order to adjust the model moisture background from the “RainSat” derived precipitation information, we need to produce best guess rainfall intensity. The traditional way to do that is to assign the average radar retrieved rain rates to the “RainSat” delineated precipitation area (e.g., the area with the probability larger than a certain threshold). This readily leads to the overestimation of light rain and underestimation of the precipitation from strong cells. An alternative scheme is to estimate the intensity of the “RainSat” based precipitation by setting different “ground truth” thresholds initially, and then running the “RainSat” algorithm repeatedly. Thus, we can determine the intensity of
precipitation according to the different probability maps corresponding to different initial thresholds. The errors for both schemes have been investigated in this chapter.

### 3.3 Regression issues

Considering that the bi-frequency distributions of VIS/IR radiances obtained at a particular place may be significantly different from those obtained in other places, errors could be caused by extending the relationship obtained within the range of the “ground truth” to regions far outside of it. The investigation of this problem is more difficult for an island country due to a lack of “ground truth” over the oceans. In this section, in order to investigate the skill of the “RainSat” technique quantitatively in terms of the distance (noted by “$D$” in this section) between the area of interest and the radar used to provide “ground truth”, single radar was used to generate the “RainSat” analysis over the entire domain. The associated nowcasting experiments were also carried out using the single radar delineated results. Other radars and the selected single radar were employed together to verify the results of the retrieved and extrapolated rainfall maps.

Table 3.1 shows the selected radars (and locations) for the same cases used in Chapter 2 (see Table 2.2). Probability maps were retrieved at UTC 2352 (day-1) for each case and the “RainSat” based nowcasts were generated based on the data at UTC 2252 and UTC 2352 (day-1). In this chapter, we approximated UTC 2352 (day-1) as UTC 0000 (day+0) for making the verifications/comparisons convenient. The rain band for each case was at least partially presented within the range of selected single stations so the “RainSat” technique could be used with sufficient ground information.

In order to show the performance of the “RainSat” technique as a function of the distance $D$, the entire experimental domain has been divided into $13 \times 13$ sub-domains with the grid length of around 150 km for each sub-domain. Skill scores, such as Critical Success Index (CSI) and False Alarm Ratio (FAR), were calculated on each sub-domain. $D$ for each sub-domain was obtained by calculating the distance between the centre of the selected sub-domain and the selected “ground truth” (radar). The maximum tested distance was set to 800.0 km in this chapter, and beyond this range, the rainfall estimates produced by the “RainSat” technique was not used.
Chapter 3. Errors inherent in the “RainSat” technique

Figure 3.1 gives the CSI and FAR scores for the “RainSat” retrieved rainfall probability as a function of different distances $D$. All scores were calculated from the probability map at the optimal probability threshold. Observations were obtained from the New Zealand National Radar Network (the probability of 100% was assigned to the observed grid point which has the reflectivity larger than 15 dBZ). The calculated scores for all sub-domains of all cases are shown by black lines (the horizontal axis indicates the distance $D$ and the vertical axis indicates the skill scores). Red lines were obtained by smoothing the black lines with a Gaussian filter at the length of 9 points, in the hope of revealing a systematic trend from the noisy data. It is apparent that within the radar range (less than 200 km), the “RainSat” technique showed relatively higher skill: CSI scores were ranged between 0.5 – 0.8 and FAR scores were also very low (less than 0.2 on average) correspondingly. However, the skills decreased drastically when the distance increased from 200 km to around 400 km: CSI dropped by around 0.6 and FAR increased from 0.2 to 0.6, approximately. After that, the skills remained stable again but at a relatively low level (CSI at about 0.2 and FAR at 0.65).

Although the “RainSat” technology has already been successfully applied in many places around the world, in order to make it clear whether it is useful in New Zealand, and show the usefulness of the “RainSat” analysis in the area of interest, we introduced a unskilled reference (Unskilled CSI: 0.02408; Unskilled FAR: 0.81301), which is the combined skill score obtained from the 6 hours nowcasts over all selected cases (see Section 2.5 for more details).

The above results show that, due to the “regression issues”, the capability of generating the accurate rainfall probability by the “RainSat” technique is largely dependent on the distance between the area of interest and the “ground truth”. However, it is still fair to say that, although the “RainSat” technique (or other satellite based methods for retrieving precipitation) may be not capable of providing very accurate precipitation estimates, it is still worthwhile to consider the implementation in New Zealand as geostationary satellite is the only tool that has the necessary coverage with relatively high temporal and spatial resolutions, and it is able to extend the availability of rainfall information out of radar range and thus it may help to improve our understanding further about the precipitation development and movement over the Tasman Sea.
Figure 3.2 gives the skill statistics for the 1-3 h “RainSat” based nowcasting generated with single radar as “ground truth”. The scores showed a very similar trend to Figure 3.1. As expected, “RainSat” performed better in the regions closest to the initiating radar station. The skills gradually decreased with the distance $D$ increased, and when the distance increased over a certain value (e.g., about 400 km in this chapter), a relatively stable but low skill score was presented. In addition, it is not surprising that the forecast skill decreased on average with the forecast lead hours increased. For example, 1 hour forecast showed the CSI scores between 0.4 and 0.9. Correspondingly, FAR increased from about 0.3 (at 200 km) to the maximum of 0.6 (500-800 km). After that, the effects of the “regression issues” became trivial gradually. For the 3 h nowcasts of rainfall probability, $D$ is no longer a major factor affecting the skill of the “RainSat” based nowcasting and both CSI and FAR presented poor scores at the high resolution of our technique. It is apparent that the dominant factor turned to be the predictability of the precipitation system itself. It is worth noting that, as the precipitation gradually moved out of the radar range, errors might have resulted when calculating the scores from the limited sampling numbers involved in the verification area.

In general, the single radar based experiments showed the effects of the “regression issues” of the “RainSat” technique and the associated nowcasting. It is apparent that, although the accuracy of the “RainSat” technique is less than radar (even for radar based precipitation estimates, the relationship between $Z$ and rain rate is still not known very well, especially for estimating instantaneous rainfall, see Table 1.2) or other direct observation instruments, by employing satellite based schemes, we are able to extend the range of the available precipitation nowcasting (e.g., from the results presented in this chapter, useful information (relative to the unskilled reference) could be obtained at the range over 400 km from the selected radar station). This is essential for New Zealand or other similar island countries. It is worth noting that currently the IR channel used in the “RainSat” technique has the wavelength of 6.5-7.0 µm, which is also known as the channel of water vapour. By coupling with other IR channels, for example the longwave IR channel (wavelength range 10.2-11.2 µm), sea surface temperature (SST) information can be incorporated in the “RainSat” technique and thus turn the original bi-frequency table to a tri-frequency table. The objective of incorporating SST is an obvious step in that it is logical to assume that higher surface temperature usually comes with higher probability of rainfall (Kumar et al.,
By involving SST information, the skill of the “RainSat” technique representing rainfall within the radar range might be improved since more constraints are added. However, the precipitation area out of the radar range could be largely underestimated according to our experiments because of the drastically decreased number of data pairs in the tri-frequency distribution table.

### 3.4 Spatial sampling related errors

The spatial resolution of the satellite data could have an effect on the skill of the “RainSat” analysis for several reasons: a significant one is that the size of bivariate frequency table can be changed with the satellite data resolution increases/decreases. For example, Figure 3.3 shows the probability distributions (> 0%) as a function of VIS (horizontal axis) and IR (vertical axis) radiances obtained from GOES satellite at 0000 UTC 30 December 2011. It is obvious that most high probability related pixels located in the “high VIS - low IR” area, which is in agreement with the assumption in the “RainSat” technique that cold (small IR) and bright (large VIS) clouds have a high probability of precipitation. However, the probability distributions for 10 × 10 km and 50 × 50 km data are obviously different: the high probability pixels for 50 × 50 km are more concentrated in the area where VIS > 17200 and IR < 9000 while the high probability pixels for 10 × 10 km are relatively more dispersed (the size of the bi-frequency table is correspondingly bigger). This data resolution resulting difference may yield uncertainties in the final “RainSat” analysis. For high resolution satellite data, the relatively large and dispersed bi-frequency distribution may cover more different combinations of VIS/IR radiances. Consequently, the probability assigned to each combination may be relatively smaller. Moreover, because more details are included in the bi-frequency table, the pairing process of the VIS/IR from other places to the table becomes more difficult. In contrast, for relatively low resolution satellite data, the bi-frequency table is relatively smaller and organized, which may be useful to provide sufficient pairs of VIS/IR data for determining the rainfall probability outside the radar range.

In order to investigate the spatial sampling related errors quantitatively, in the study the following statistical scores were used to evaluate the skill of the “RainSat” retrieved and extrapolated precipitation: Frequency Bias index (FBi, or Frequency Bias), Root Mean Square Error (RMSE) and Correlation Coefficient. These scores were not only calculated
within the range of the radar(s) used to train the system, but also used to investigate the skill of the “RainSat” technique in the area out of the “ground truth” coverage. In this thesis, TRMM Multi-satellite Precipitation Analysis (TMPA) were used as the “truth field” in the verifications out of the radar range.

It is worth noting that, the footprint of TRMM PR does not cover most areas of New Zealand and the relevant areas of interest over the Tasman Sea. TMPA refers to the merged products based on the TRMM and other satellites precipitation products. This process is usually described as the algorithm of 3B42. Detailed descriptions about the 3B42 algorithm can be found in Huffman et al. (2007, 2013).

Detailed information about the calculation of skill scores is given in Appendix B, here we give a general introduction of different scores.

FBi is the score that used in NZ MetService for the evaluation of NWP products. It is set up based on the agreement between the forecast F and observation O on each grid point. If FBi is greater than 1, the event is overestimated otherwise the event is underestimated.

RMSE is another widely used score for evaluating the impact of data spatial resolution on rainfall forecasts and observations (e.g., Shucksmith et al., 2011). The differences between the estimated values and the values actually observed can be measured by using RMSE quantitatively. Similar to FBi, RMSE ranges from 0 to $\infty$ as well while the perfect score is 0. In this study, RMSE was used to evaluate both the “RainSat” retrieved rain rates and the rainfall probability. When evaluating the “RainSat” retrieved rain rates, the average radar observed rain rates were assigned to the pixels (in the satellite retrieved rainfall map) where the predicted (retrieved) rainfall probability was greater than the estimated optimal probability threshold. When evaluating the “RainSat” rainfall probability analysis, the pixels (in radar retrieved rainfall map) with radar observed reflectivity (larger than a certain threshold) were assigned the 100% probability of rainfall (similar to the approach used in the verification of Section 3.3).

The correlation coefficient is designed to describe the proportion of observed data that can be explained by the forecast. It also has been widely used to investigate the uncertainties inherent in very short term forecasting resulted for radar data sampling errors (e.g., Grecu
and Krajewski, 2000). Usually, higher correlation coefficient refers better rainfall estimates.

It is worthwhile to note that none of above scores (or other similar skill scores) are able to measure how well a method is in representing or predicing a precipitation system in absolute terms since the skill scores are very resolution sensitive. However, they provide a method to evaluate different schemes using similar input data objectively.

3.4.1. The impact of spatial resolution on “RainSat” rainfall delineation

Figure 3.4a shows the impact of different spatial resolutions of satellite data on the accuracy of the “RainSat” retrieved probability. All radars operated by NZ MetService were used to generate the “RainSat” analysis and the verifications were carried out within radar range. All scores were calculated in terms of both probability and intensity and combined over all selected cases (for the probability assessment, the grid points with radar observed reflectivity larger than 20 dBZ were assigned to 100% probability of rainfall). The spatial resolutions of satellite data were sampled with a resolution of 8 - 50 km using a simple linear interpolation method. Spatial averaging process was applied for all lower resolution cases (> 8km) and the verification was carried out using smoothed radar data at 8 ×8 km (Shucksmith et al., 2011).

Not unexpectedly (e.g., Seed, 2003), from Figure 3.4a, lower resolution satellite data were able to provide slightly higher skill scores on average. For example, the ”RainSat” technique provided the correlation coefficient (intensity) of 0.41 with the spatial resolution of 8 km and the score increased to around 0.425 when the resolution decreased to 50 km. Here the intensity assigned to the “RainSat” analysis was taken from the average radar reflectivity used to train the VIS/IR radiances. For the frequency bias statistics (intensity), the score decreased from 2.14 (for the resolution of 8 km) to 2.1 (for the resolution of 50 km) approximately. Similar results also could be found from the scores for the probability analysis of frequency bias. However, the relationship was not always like this. For example, from all statistical scores, the satellite data with the resolution of 40 - 45 km provided better results compared to the data with the resolution of 50 km due to the reduction in the available data size.

From frequency bias statistics, we can clearly find that, compared to radar observation, precipitation was overestimated by the “RainSat” technique. Several reasons may lead to
that. For example, the fields that the satellite measures were based on the cloud characteristics at the top of clouds, which do not necessarily reflect the situation that occurred at the height of radar observation. Another significant reason could be attributed to the error existing in the process of estimating optimal probability threshold: obviously, underestimated optimal probability threshold may lead to overestimated rainfall area on average.

Generally, it is reasonable to say that the “RainSat” technique is better at delineating relatively large scale rainfall systems. However, it is worth noting that, since there are no direct observations over the Tasman Sea, all of the scores presented by Figure 3.4a were calculated within the range of “ground truth” (radar), the errors of the “RainSat” technique in the area out of the radar range may be different (e.g., representatively errors). As in the last chapter, in order to investigate the skill of the “RainSat” technique over the sea, we used single radar as “ground truth” to produce the “RainSat” analysis over the whole New Zealand, and then applied all radars to verify the generated "RainSat" analysis (Figure 3.4b).

When selecting the single radar (“ground truth”) for the implementation of ”RainSat”, the main criteria was that the target rain band must be clearly presented (or at least partly presented) within the coverage of the selected single stations. Compared to the results obtained by using the National Radar Network as “ground truth”, it has a similar trend that the skill of “RainSat” increased on average with the spatial resolution of satellite decreased. However, we find that, from the global sense scores that the maximum correlation coefficient (for probability) decreased from around 0.38 (all radars) to 0.305 (single radar) and the minimum of RMSE (for probability) increased from around 0.30 (all radars) to 0.35 (single radar). This indicates that, similar to the results presented in the last section, because of the “regression issues”, the skill of “RainSat” on representing the rainfall characteristics would decrease when extending the “ground truth” based bivariate frequency table to other places. It is worth noting that the ratio of estimated precipitation area was decreased in frequency bias, and it indicated that (1) compared to the results initiated with all radars, smaller precipitation area might be estimated out of the radar range.

Normalized Root Mean Squared Error (NRMSE), which was used in Shucksmith et al. (2011), was applied in this section to quantify the adjustment for the “RainSat” retrieved
precipitation caused by the different spatial resolutions of satellite data. NRMSE is calculated based on Equation 3.1:

\[ NRMSE = \sqrt{\frac{\left( L_i - H_i \right)^2}{\langle H_i \rangle}} \]  

(3.1)

Where \( L_i \) and \( H_i \) are the retrieved intensity (or probability) in a single pixel from the downgraded and original resolution (in this chapter, the original resolution was set to 8km \( \times \) 8km), respectively. Figure 3.5 gives the NRMSE statistics at different resolutions in terms of intensity and probability. It is clear that the spatial sampling resulting uncertainties were not significant: the NRMSE statistics for both intensity and probability were always less than 2.5%, which indicates that the skill of the “RainSat” technique was not be adjusted substantially with the changes of the resolution for input data.

### 3.4.2. The effect of the spatial scale of satellite data on “RainSat” based nowcasting

Considering the limited predictability of small scale information observed by radar, in a radar-based extrapolation scheme, the importance of eliminating small scale information has been discussed often (e.g., Wilson, 1966; Bellon and Zawadzk, 1994; Seed, 2003). In the satellite based extrapolation scheme, similar issues also exist. However, it is reasonable to assume that, compared to radar observation, satellite data, especially the “RainSat” retrieved precipitation, has very limited capability to represent the variety of small scale structures present in the scene, and thus the issues inherent in data spatial averaging processes may be not as significant as in radar echo extrapolation.

In order to investigate how the spatial resolution of satellite data affects the “RainSat” based nowcasting, the cross-correlation technique was applied to generate the “RainSat” based forecasts up to 3 hours (30 min, 60 min, 90 min, 120 min, 150 min and 180 min). Motion vectors were spatially averaged using the Gaussian smoothing technique at the length of three grids. All verifications were carried out within radar range. As in the last section, the original spatial resolution (8 \( \times \) 8 km) has been downgraded to 50 \( \times \) 50 km gradually with an interval of 5 km.

Figure 3.6 gives the skill scores considering both the different spatial resolutions and forecast lead times. It is obvious that, similar to above, all scores showed that the forecast skill increased on average with the decreased spatial resolution of satellite data. For
example, the correlation coefficient (intensity) increased from the mean (combined over all forecasts) of 0.28 (8 km) to about 0.31 (50 km) and the RMSE (intensity) dropped slightly from the mean of 7.2 (8 km) to 7.0 (50 km). This is in good agreement with the results obtained in Figure 3.4 and the cited papers about the investigation for radar based very short term QPF (e.g., Seed, 2003; Grecu and Krajewski, 2000).

In Figure 3.7, the average spatial - temporal NRMSE diagram shows the errors distributed in terms of different satellite data resolutions (horizontal axis) and forecast lead times (vertical axis). It is apparent that different resolutions resulted a maximum of 10% difference in the extrapolation based nowcasts, which was much higher than the NRMSE obtained only for the “RainSat” retrieved rainfall (< 2.5%). However, compared to the similar investigations with radar based nowcasting (e.g., Grecu and Krajewski, 2000), the resolution induced error inherent in the “RainSat” based nowcasting was not significant. A reasonable explanation is that, by setting the highest resolution as 8 km, most small features of precipitation, which have the highest possibility of reducing the predictability of nowcasting, have already been removed. The precipitation system which with the scale larger than 10 km is relatively stable and organized, and thus it can be better predicted relative to those small but strong cells.

Moreover, with the lead time increased, the bias caused by the different resolutions reduced. When the lead time was greater than 2 hours, the impacts of the initial satellite data resolution became relatively trivial. This shows that the, after 2-3 hours, the dominant error in the “RainSat” based nowcasting is no longer the errors from the initial satellite but largely determined by the characteristics of the precipitation system itself.

In order to investigate the impact of different spatial resolutions of satellite data on the “RainSat” based nowcasting further, the Normalized STandard Deviation (NSTD) was calculated using Equation 3.2.

\[ NSTD(S)_t = \frac{\text{std}(S)_t}{\text{min}[\text{std}(S)]]} \]  

(3.2)

Where \( S \) is the skill score in terms of different resolutions, standard deviation (\( \text{std} \)) was calculated at the lead time \( t \). \( \text{min}[\text{std}(S)] \) represents the minimum standard deviation for the entire forecast period. The NSTD distribution as a function of forecast lead time is
shown in Figure 3.8.

In Figure 3.8, higher NSTD magnitude means that the adjustment caused by the different initial resolutions of satellite data is more significant. Obviously, the NSTD decreased for all skill scores (FBi, RMSE-intensity, RMSE-probability and correlation coefficient) with the lead time increased on average. The minimum NSTD(S) for almost all scores were presented at the lead time of 180 min and the highest NSTD(S) were usually presented at 30 min. The statistics of NSTD was in agreement with the evaluation of Figure 3.7, that the impact of initial field resolutions on extrapolation based nowcasting reduced gradually as the forecast lead time increased.

From above discussions, we can identify the uncertainties caused by the different sampling scales for the “RainSat” technique. Only about 2.5% NRMSE was introduced by the changes of the resolution for initial satellite data. Coupled with the errors inherent in the nowcasting technique (like the cross-correlation technique used in this chapter), the NRMSE in the “RainSat” based nowcasts could contribute up to 10% for the lead times less than 30 min. After that, the differences caused by the changes of the resolution for satellite data decreased gradually and, after 3 hours, the associated NRMSE reduced to a maximum of about 6%. Generally, the effects of the initial spatial resolution of satellite data on the “RainSat” retrieved precipitation analysis and the “RainSat” based nowcasting were not significant. However, lower resolution of satellite data was still more likely to yield better rainfall estimates.

3.5 The height of the “RainSat” retrieved precipitation

In order to use the “RainSat” analysis to initialize NWP models in New Zealand, the effective height of the “RainSat” analysis must be determined. In the “RainSat” technique, the cloud top height (CTH) was traditionally assumed the height corresponding to the retrieved precipitation probability. A straightforward method was applied to determine the cloud top height: the “RainSat” height is assigned by searching the model background temperature profile from the bottom level (k=0) to the top (k=T), and a level with a temperature matching, or has the smallest difference compared to, the satellite retrieved brightness temperature was assigned to the “RainSat” probability map.
However, there are several reasons why this may lead to a poor height estimate. Since CTH is calculated based on the estimated temperature from the NWP model and satellite, the errors of the NWP model and the brightness temperature retrieved from satellite could be accumulated and propagate to the calculated CTH magnitudes. Figure 3.9 gives an example of the estimations of temperatures in the WRF and satellite data. The solid line indicates the in-situ temperatures observed at Auckland at 0000 UTC 01 November 2011, while the WRF simulated temperatures and satellite retrieved cloud top temperature are represented by a dot line and an asterisk line, respectively. It is worthwhile to mention that all available stations in the area of interest have been adopted for the similar comparisons, and most of them showed similar results as Figure 3.9.

It is apparent that, for this case, WRF presented a good simulation in temperature compared to the associated observations (relative to the simulations for most other fields), especially at relatively lower levels (e.g., the height less than 5,000 m). Similar results were found from other stations used in this evaluation (figures not shown). From Figure 3.9, according to the satellite retrieved cloud top temperature (CCT), we can estimate that the cloud top should be around 4000 m. Due to the high correlation between model simulated and actual observed temperature profiles, we may attribute the main factor resulted the errors in the cloud top height estimates to the errors in satellite brightness temperature estimate, which is calculated based on empirical relationships.

The height of the “RainSat” rainfall is expected to be determined by both the satellite retrieved CTH and radar retrieved echo top height (ETH) together, and usually the less difference between ETH and CTH, the higher accuracy of the estimated height for the “RainSat” analysis. However, the fact is that if the difference between ETH and CTH is significant, this may lead to significant errors when assimilating the “RainSat” analysis into the NWP model at the level of cloud top. Figure 3.10 gives three examples of the comparisons between CTH and ETH obtained at 0000 UTC 01 November 2011, 0000 UTC 31 December 2011 and 0000 UTC 07 January 2012. The left column gives estimates of radar derived ETHs and the right column shows the associated CTHs retrieved from the satellite. We can see that there is significant difference between them. From the results of more cases, we conclude that, for most cases, ETH is much lower than CTH, which can be easily understood, since the cloud may be optically thick at an altitude significantly above the actual height of the radar detectable precipitation due to small particle growth processes.
In addition, as the distance from radars increases, the ability of the radar to estimate echo heights decreases due to the adverse effects of beam spreading.

It is worth noting that ETH was calculated within a volume scan by determining the maximum elevation angle at which dBZ > 18 was detected, the standard atmospheric refractivity was considered during the data process. Details about how to calculate ETH can be found from Lakshmanan et al (2013).

In order to investigate the difference between ETH and CTH quantitatively, the distributions of the height difference calculated over all selected cases are shown in Figure 3.11. About 60% of the grid points had differences less than 3.0 km and about 35% had differences less than 2.0 km. In contrast, only about 8% and 10% of grid points showed the difference less than 500 m and larger than 5.0 km, respectively. Moreover, it is clear that with the distance between radar and the area of interest increased, the difference decreased in general (see Figure 3.12). The results showed that within the range of 50 km, the height differences for most grid points were larger than 5 km while within the range of 150-200 km, most differences ranged from 0.5 to 3 km. However, it is worthwhile to note that at far range the radar has limited ability to estimate rainfall heights due to beam width limitations.

Figure 3.13 gives an example of the height differences between two adjacent vertical layers obtained at 0000 UTC 21 November 2011 for the WRF vertical configurations with a total of 39 layers (the top pressure is 50 hPa). We find that, since the maximum height difference is less than 1.2 km, the difference of 2-3 km (or even larger) between ETH and CTH may lead to significant displacement errors in the vertical. Considering in the nudging system, which is described in a later chapter, the vertical influential radius is usually set to 0.1 η (height from about 1.0 km to 4.0 km). Wrong weighting factors may be assigned vertically and therefore lead to incorrect adjustments for precipitation affected fields in the model.

In this chapter and following studies with the “RainSat” analysis, we adopted the Effective Height (EH), which is the average height calculated between CTH and ETH, to represent the height for the “RainSat” retrieved precipitation. We may consider it as the most straightforward approach to reduce the displacement errors caused by the bias between radar estimated ETH and satellite estimated CTH.
3.6 “RainSat” derived rain rates

The main objective of the “RainSat” technique is to produce precipitation probability maps, however, in order to use the “RainSat” analysis to initialize the NWP model for improving (very) short range QPF, it is necessarily to determine the rain rates corresponding to the delineated probability. There are several methods to achieve that: one is assigning the average radar derived rain rates to the “RainSat” map, which was employed by the group of the Stuart Marshall Radar Observatory at McGill University, Canada. There are several drawbacks to this method: (1) light rain or drizzle may be significantly overestimated and lead to false warning in such regions and (2) strong cells or hails may be underestimated, which may lead to significant consequences in flooding or other similar urban forecasting and management. This method (noted as Method 2 in this chapter) was evaluated quantitatively and the verifications were carried out against both radar and TMPA. We also proposed an alternative method, which determines the “RainSat” retrieved rain rates by initially setting different radar thresholds for generating different “RainSat” probability maps correspondingly. The results from this method (Method 1) have also been verified using both the radar and TMPA. Different scores (RMSE, MAE, FBi and correlation coefficient) were calculated for these two methods. For the evaluations using radar data, the verification area was limited in the radar range and for the evaluations with TMPA, the verification area covered most regions over the Tasman Sea including New Zealand.

Figure 3.14 shows the correlation coefficients for the “RainSat” retrieved rain rate in terms of the threshold of 0.02 $mm h^{-1}$. From the viewpoint of the entire radar coverage, it is apparent that, compared to radar observations, method 1 is capable of providing slight improvements compared to method 2 for almost all selected cases. In contrast, in the regions out of the radar range, two methods provided very similar results (for certain cases, Method 2 even performed better than Method 1) in comparison with the verifications against the TMPA analysis. From Figure 3.15, we find similar trends from the scores of RMSE and MAE as both methods provided similar skills. From Frequency Bias index, two schemes provided the exact same skills. In addition, from FBi we find that the precipitation was generally underestimated in the regions out of the radar range. When the threshold was increased to 0.5 $mm h^{-1}$ (Figure 3.16), Method 1 provided relatively lower RMSE and MAE for most cases in comparison with Method 2 within radar range. Whist using the
Chapter 3. Errors inherent in the “RainSat” technique

TMPA analysis as “truth fields”, the two methods presented trivial differences. By using the FBi scores, it is apparent that Method 1 provided much better results in contrast to Method 2. For the FBi obtained using radar as the "truth field", Method 2 largely underestimated the precipitation for most cases (FBi scores are almost zero) except for three cases (Case 5, 8 and 10) while the precipitation for these three cases were overestimated. For example, for Case 8, FBi score for Method 2 was about 2.5, and it is much higher than the perfect score 1 (the associated score for Method 1 was about 1.25). In contrast to the verifications against radar data, in the regions out of the radar range, Method 1 still underestimated the precipitation for almost all events, and the results from Method 2 were very similar to that verified against radar. From Figure 3.17, which shows the verifications with the threshold of 2.0 $mm h^{-1}$, more significant differences between Method 1 and Method 2 were presented. For RMSE statistics, Method 2 showed much higher biases compared to Method 1 within the radar range. For the RMSE calculated using TMPA, Method 1 also presented better skills for most cases. Very similar results were found from the MAE statistics, the errors led by the use of average radar derived rain rates achieved 1.5 $mm h^{-1}$ (against radar) and 1.0 $mm h^{-1}$ (against TMPA). The reason for the very high RMSE and MAE for Method 2 can be seen in the FBi statistics: we find that Method 2 was not capable of delineating precipitation with the threshold larger than 2 $mm h^{-1}$ as the radar derived average rain rates were less than 2 $mm h^{-1}$ for all cases.

Overall, according to the statistics shown from Figure 3.15 to Figure 3.17, we find that for light precipitation, Method 1 and Method 2 provided very similar delineations, while for relatively heavier precipitation, the new method (Method 1) generated better results compared to the traditional one (Method 2). However, it is apparent that significant errors still existed for Method 1, especially for heavy rainfall events, which agrees with the previous studies in that the “RainSat” technique is much better at delineating precipitation location rather than the intensity, even using a relatively more complicated algorithm.

3.7 Conclusions

By providing additional rainfall information, the implementation of the “RainSat” technique in New Zealand would be helpful to the further understanding of precipitation initiation and development over the Tasman Sea, in regions mostly out of the range of New Zealand National Radar Network. In this chapter, four main factors that may affect the skill
of the “RainSat” technique have been discussed, which are an essential precursor for the operational application of the “RainSat” scheme in the future.

First, the “regression issues” were investigated. We find that as the distance between radar and the verification grid point increased, the “RainSat” skill decreased significantly. According to the CSI and FAR statistics, when the distance increased beyond about 200-400 km km, the skill of the “RainSat” technique became poorer. Similar results could be found from the “RainSat” based nowcasts, especially for the lead times of the first 1-2 h. After that, the error caused by the “regression issues” was not the dominant factor affecting the accuracy of nowcasting.

Second, the effects of the spatial resolution for satellite data on the skill of the “RainSat” technique have been discussed. Satellite data with high resolution are expected to provide more detailed delineation for the structure of rainfall. However, high resolution satellite data may also yield more dispersed bi-frequency distribution of IR and VIS radiances, which can lead to a more serious “regression issues” in the areas out of the radar range. The results showed that, low resolution satellite data presented slightly better probability estimates, which indicates that the “RainSat” technique is better at delineating large scale rainfall systems rather than the small but intense rainfall cells. Similar results were also found from the “RainSat” based nowcasts, and this is in good agreement with a number of previous studies, which stated that the predictability of weather system increases as the data spatial scale increases. However, the difference are not significant as the maximum of NRMSE was less than 10%, which is much smaller compared to the similar studies carried out using radar data (e.g., Shucksmith et al., 2011).

Third, the errors in estimating the height of the “RainSat” analysis have been investigated. The errors of the “RainSat” height are largely determined by the difference between ETH estimated by radar and CTH obtained from satellite. From the statistics, the difference between ETH and CTH were largely dependent on the distance between radar and the verification grid point. For the short range, due to the limited elevation used, the top of precipitation systems, especially for strong convective activities, was often underestimated by radar. In this chapter, we proposed to assign the Effective Height (EH) to the ”RainSat” analysis, but it is still worth mentioning that considerable errors may still exist especially when we use the “RainSat” analysis to adjust the model background with high resolution in
vertical.

Finally, the errors in the “RainSat” estimated rain rates have been investigated. Two methods were used to estimate the “RainSat” based rainfall intensity. Method 1 estimated the rain rates by employing different probability maps corresponding to different “ground truth” thresholds. Method 2 simply assigned the radar derived average rain rates to the “RainSat” delineated probability map. Both methods have been evaluated using the observations from radar and TMPA. The results showed that for light precipitation, both methods gave very similar skills while for relatively heavier precipitation: Method 1 has the capability of presenting better results, although the skills for both methods were poor. For the verifications within the radar range, the precipitation was overestimated by Method 1 for most cases, while for the comparisons with TMPA, the precipitation for most cases were underestimated.

As the next step, the “RainSat” retrieved rain rates are expected to be used to initialize the NWP model over the Tasman Sea. Based on above discussions, it is worthwhile to note that, although “RainSat” is able to provide relatively higher temporal resolution precipitation estimates, it is not appropriate to expect that it is able to represent the small-scale and intense convective activities very accurately. However, the capability of adjusting the clouds/precipitation affected backgrounds in a model is still expected to provide significant benefits to QPF in New Zealand, certainly compared with knowing nothing at all over the Tasman Sea.
Chapter 4. Combining radar and satellite data to improve nowcasting

4.1 Abstract
Extrapolation based nowcasting using radar data is considered an effective way to provide 0-2 h precipitation forecasts compared to NWP models. However, due to the limited radar range, the errors caused by the incomplete observed radar echoes in nowcasting, especially in the region near the edge of the radar range, are still not well investigated quantitatively. The errors can affect both the estimated precipitation area and motion vectors and thus may lead to significant loss on the skill of extrapolation based nowcasting. In this chapter, we employed the “RainSat” technique to delineate precipitation out of the radar range. By merging the “RainSat” analysis with radar data, the extrapolated motion vectors and precipitation area were adjusted well, and therefore largely reduced the errors caused by the use of the incomplete radar echoes alone. Two examples were presented in detail. Verifications for both the traditional method and the method combining radar and satellite analysis were carried out using different objective forecast skill scores.

4.2 Introduction
Nowcasting usually refers to 0-2 h precipitation forecasting, which is usually carried out by using simple extrapolation or other similar straightforward approaches (Wilson et al., 1998). During last several decades, there are a number of methods used for extrapolating precipitation based on radar echoes. The early attempts used an average motion vector over the entire area of interest to advect the storm position at subsequent 0-3 hours (e.g., Ligda, 1953; Hilst and Russo, 1960). Such a scheme has been applied to the world’s first operational nowcasting system SHARP, which was operated at McGill Weather Radar Station since 1976 (Austin et al., 1987). Techniques based on multiple motions vectors were first developed by Rinehart and Garvey (1978) using the cross-correlation approach. Nowcasting based on cross-correlation is usually very reliable and can be adopted for a wide range of precipitation systems, the main drawback of the cross-correlation approach is that, depending on the target resolution of the derived motion vectors, the advection process can make such approach very computationally expensive (e.g., Ruzanski, 2010). Nowcasting based on the tracking of individual cells was also developed since the 1970s (Wolf et al., 1977; Dixon and Wiener, 1993). One good example of such scheme is the
Thunderstorm Identification, Tracking, Analysis and Nowcasting (TITAN) system developed by NCAR since the 1990s. The TITAN system is robust at predicting strong, well defined and behaved storm structures but usually performs poorly on weak and stratiform precipitation systems (Ruzanski, 2010). In addition, the handling of the echo splitting and merging is always very difficult for the cell tracking methods. Statistical models were also used in nowcasting recently (e.g., Seed, 2003 and Xu et al., 2005). These methods give the possibility of taking physical knowledge of atmospheric dynamics into account and they usually can be performed with very economical computational resources. In order to extend the effective period of nowcasting, simple extrapolation based nowcasts are merged with outputs from NWP models to generate 6 hours seamless precipitation forecasts. The first system using such scheme is likely to have been the NIMROD system operated at the UK Met Office (Golding, 1998). Other similar systems, like Autonowcaster (Mueller et al., 2003) and STEPS (Bowler et al., 2006), were developed and have been operated in many countries during the last decade. Detailed descriptions of the development of nowcasting can be found from Chapter 1.

Currently, NZ MetService runs eight Doppler C-band radars. The spatial resolution of the radars is range-dependent from about 150 m to a few kilometres and around 7 minutes in time with 7 levels, which is sufficient to characterize most types of precipitation. The scan covers an area out to a range of about 480 kilometres. The National Radar Network not only covers all metropolitan areas and most coast regions of New Zealand, it also provides limited offshore forecast ability that extends the availability of high resolution observations to the maximum about 200 km out of the coast. The Severe Weather Warnings (SWW), specifically for thunderstorms in New Zealand, are issued by expert forecasters, who use the TITAN system as guidance. Other schemes, like the “spectral prognosis” algorithm developed by Seed (2003), are also used for research in NIWA (Gray et al., 2005).

It is apparent that all of these approaches used in New Zealand or other countries rely on the fully observed radar echoes. Significant errors would be introduced in nowcasting if the precipitation system can only be partially captured. For example, in the TITAN system, volumetric centroid and reflectivity-weight centroid may be estimated in wrong positions, and the precipitation area may be underestimated depending on the incomplete echoes observed. The problem usually happens when the echo is located at the edge of the radar range, or using smaller radar (e.g., x-band radar used for hydrology purpose) for observing
Chapter 4. Combining radar and satellite data to improve nowcasting

the relatively large scale precipitation system. In order to address this problem, the range of precipitation monitoring network must be extended and it is apparent that the use of satellite data can be considered as an additional approach to delineate precipitation effectively. In this chapter, we used the “RainSat” technique to delineate the rain band out of the radar range. The reason for using the “RainSat” technique is that the technique estimates precipitation trained by the observations from radar, which means that the “RainSat” based precipitation is usually able to provide higher correlation to the associated radar data relative to other precipitation retrieval algorithm based on satellite alone, especially in the area not very far away from radar station (see Chapter 2 and 3). The “RainSat” analysis was coupled with radar data in this chapter, and the merged analysis was expected to give enhanced capability to capture the full rain band and therefore yield more accurate estimates in rainfall properties for the purpose of nowcasting.

4.3 Errors inherent in extrapolation based nowcasting

There may be many errors inherent in generating radar based nowcasting. One main problem is that the individual cell may be not fully obtained since there is no information available out of the radar range. For example, in Figure 4.1 (left), because the echo at (T-1) cannot be delineated completely by radar, the dBZ weighted centre can be estimated in a wrong position (noted B) as the actual dBZ weighted centre should be located outside of the radar range (noted A). Assuming that we have the echo at the subsequent time T, which can be delineated completely by radar with the weighted centre C, it is clear that different motion vectors can be obtained from A (or B) to C (AC vs BC). This difference can be appreciated in the extrapolated dBZ weighted centre ($\hat{A}$ vs $\hat{B}$), which may lead to significant errors in the associated nowcasting. In addition, Figure 4.1(right) shows another error may be caused by using the incomplete radar echoes. In the figure, the precipitation systems cannot be delineated completely at both (T-1) and (T+0). However, it is apparent that the area of extrapolated precipitation at (T+1) is largely dependent on the precipitation area at (T-1) and (T), therefore besides the wrong estimated location of the dBZ weighed centre, in such case the predicted echo area at (T+1) would be underestimated.

Another very serious problem may exist for small high resolution x-band radars used to study hydrology. Because of the very limited radar range, the radar may be not able to track the same system over a particular short period. For example, for the x-band radar
operated at the University of Auckland, New Zealand, the maximum range chosen can be as little as 40 km in order to achieve high spatial and temporal resolution and thus in the successive two images, different systems may be captured. For example in Figure 4.2, at (T-1), system A is observed while at (T), another system B, which is moved from outside of the radar range is observed. This means that there are actually two different systems obtained in the images at (T-1) and (T). It leads to a very wrong motion vector estimate, which has the opposite direction to the one it is supposed to be (the wrong predicted system is noted as C (T+1)).

Overall, a not fully described echo may result in considerable errors in estimating the precipitation properties including reflectivity weighed centroid, precipitation volume and intensity, and these errors can lead to poor skill of the associated nowcasting for subsequent hours.

4.4 Methodology

The procedure for combining radar data and the “RainSat” analysis can be described in Figure 4.3: (1) satellite data is used to delineate a precipitation probability map. According to the probability map, the associated rain rates map can be produced. (2) The cell (object) recognition technique (e.g., Dixon and Wiener, 1993) is employed to recognize different individual rain bands/cells obtained from both radar and the “RainSat” analysis, respectively. For example, in Figure 4.3, “Sat_cell” 1-3 represent the three individual cells obtained from the “RainSat” analysis, and “Rad_cell” 1-2 represent the two cells recognized from the associated radar image. (3) The boundary for each radar cell is obtained using the Moore-Neighbor tracing algorithm modified by Jacob’s Stopping criteria (Gonzalez et al., 2004) and then (4) we need to calculate the distance between each grid point of the boundaries (e.g., Rad_cell1 and Rad_cell2) and the radar range, the distance can be noted as “d(x)” here, x is ranged from 1 to n, where n is the number of grid points on the boundary lines for each radar derived cell. We assume that n_p represents the number of grid points with “d” less than 5 km, in this chapter, if n_p/n > 30%, the target radar derived cell was recorded. For example, “Rad_cell1” is selected and considered as an incomplete cell observed. (5) At the next step, the proportions of the “RainSat” analysis within the radar range (Sat_cell1’ and Sat_cell2’) are compared to “Rad_cell1”, the associated correlation coefficients (Cc1 and Cc2) are calculated, the cell (e.g., Sat_cell1’ in
this chapter) of the “RainSat” analysis with the highest correlation coefficient is selected. As the last step, “Sat_cell1” and “Rad_cell1” are merged (Step 7 in Figure 4.3) and the combined analysis, which includes the merged analysis and “Rad_cell2”, is then applied to the nowcasting technique. It is worthwhile to mention the reason why Sat_cell2 is not included. The main purpose of this approach is to provide a complete description of the main rain band which has already affected the area of interest. Moreover, Sat_cell1 is well trained by the radar data therefore it can be considered to be higher quality data than Sat_cell2, which is further from the radar.

It is worth mentioning the limits of the scheme. First, since the resolution of satellite data is usually lower than that of radar data, the spatial resolution of the combined analysis is more likely to be the same one as the “RainSat” analysis, it may cause the loss of small features observed by radar observation. Second, although we consider the “RainSat” analysis could provide high correlation compared to the associated radar data, the intensity estimated by the “RainSat” technique may still include significant errors (the details about the errors of rainfall intensity inherent in the “RainSat” analysis can be found from Section 3.6). Therefore, the discontinuity of the combined analysis in the joint area may lead to uncertainties and affect the skill of the nowcasting technique. Third, the “RainSat” technique estimates rainfall from the radar observed information at the echo top height and the satellite observed IR/VIS from the cloud top height, there are significant errors in estimating the height for the “RainSat” analysis (see Section 3.5) and the “radar+RainSat” combined analysis correspondingly. Applying the effective height might be able to reduce such error to some extent (See Section 3.5).

4.5 Results

In this chapter, we presented two rainfall events to show the errors inherent in the radar alone extrapolation scheme and the improvements made by involving the “RainSat” analysis. The radar operated at Palmerston North (PN) provided the “ground truth” for the “RainSat” technique. Different skill scores, including the biases in echo area and reflectivity weighted echo centre, Probability of Detection (POD), Equitable Threat Score (ETS), False Alarm Rate (FAR) and Frequency Bias index (FBi), were used to evaluate both the traditional radar alone and the new developed “radar+RainSat” schemes.
During the pre-processing procedures, the resolution of radar reflectivity data was downgraded and gridded to 10×10km, which corresponds to the scale of most organized rainfall systems other than isolated thunderstorms. Relatively large scale and more organized patterns result in the time scale of validity of linear extrapolation to be of the order of 1-2 hr on average (e.g., Wilson et al., 2010). Satellite data obtained from GOES-imager, which usually has the resolution from about 4-15 km, was also interpolated at the spatial separation of 10 km and therefore the spatial resolution of the “RainSat” analysis used in this chapter was consistent. The time interval for involving data to generate nowcast was 1 hour, and the verifications were carried out for the subsequent 6 hours of forecasts.

4.5.1. Case 1: 01 November 2011

From 31 October 2011, a wide spread rain band initiated over the Tasman Sea and moved eastward to New Zealand. From about 1100 UTC 31 October, the radar operating in Palmerston North first observed relatively high reflectivity. Then the observed rain band gradually strengthened and brought significant rainfall over the North Island and the top of the South Island over next about 24 h. The intensity of precipitation reduced from about 1100 UTC 01 November, and the main rain band moved out of the radar range after 1700 UTC 01 November. Figure 4.4 shows the reflectivity obtained from radar, the “RainSat” analysis and the combined analysis for Case 1. We find that the rain band was moving towards the west coast of the North Island. However, from radar observations, only a very limited area of the rain band has been presented compared to the associated “RainSat” analysis. In addition, there are many spurious rainfall areas estimated by the “RainSat” analysis. In contrast, the combined analysis showed a relatively whole rain band with fewer false warnings.

Figure 4.5 shows the motion vectors retrieved from radar and the “radar+RainSat” analysis. In order to view the vectors clearly, the graphs were plotted with the resolution of 15 km. It is apparent that the combined analysis provided vector estimates over a larger area. For the vectors plotted based on radar alone, the old cell obtained at 2300 UTC moved eastward towards the West Coast of New Zealand and the cell that appeared in the region near the radar range at 0000 UTC was considered as newly developed, thus the associated vectors near the radar range were nearly zero. In contrast, the combined analysis provided very similar results in the area of the west coast of the North Island, New Zealand compared to
the derived vectors from radar, and in the area near the radar range, none zero vector estimates were generated, which are more realistic. This suggests that significant errors in estimating motion vectors could be caused by using incomplete echoes. By coupling the “RainSat” analysis with radar data, this error was reduced.

Figure 4.6 gives the comparisons between radar alone and the “radar+RainSat” analysis based nowcasts over 1-3 hours. The associated observations are shown the right column. It is apparent that the radar alone extrapolation underestimated the precipitation area on average, especially with the lead time increased to 3 h. Although the merged analysis based extrapolation still could not provide very accurate precipitation nowcasting, its forecast skill was obviously higher than the one generated by radar data alone.

Because of the underestimated motion vectors near the edge of radar range, the precipitation estimated by the radar alone showed very slight movement, and it mainly distributed in the area about 150 km out of the West Coast of the North Island over the entire 3 hours. In contrast, precipitation apparently moved eastward from (T+1) to (T+3) by employing the “radar+RainSat” analysis, which was more realistic in comparison with the associated observations.

The biases (mean absolute offsets) for reflectivity (dBZ) weighted echo centre between the observed and extrapolated precipitation for both the radar alone and the combined analysis (with the threshold of 15 dBZ) are shown in Figure 4.7. It is evident that the bias for the combined analysis was relatively smaller than the one obtained from the radar alone approach. The difference increased on average as the lead time increased. For example, at the first hour, the bias difference was less than 10 km. While at the lead time of 4 h, the difference was over 30 km. It is straightforward to understand: the initial errors in the estimated dBZ weighted echo centre can be accumulated and lead to considerable errors as the forecast time increases. Similar results can be found from Figure 4.8, which shows the precipitation area biases calculated for both nowcasting schemes.

Overall, we find that the “radar+RainSat” analysis has the capability of reducing the errors in both rainfall area and intensity-weighted echo centre estimates. However, it is worth noting that the errors were still significant even using the additional “RainSat” technique in nowcasting. It is apparent that, the limited predictability of precipitation system using a
relatively simple extrapolation technique is still a dominant factor affecting the skill of nowcasting.

Figure 4.9 shows the forecast skills in terms of different verification thresholds (0.2 \( mm \) h\(^{-1}\), 0.5 \( mm \) h\(^{-1}\), 1.0 \( mm \) h\(^{-1}\) and 2.0 \( mm \) h\(^{-1}\)). From Probability of Detection (POD) statistics (left-top), we find that the combined analysis has the capability of providing more correctly predicted grid points at relatively small threshold (from 0.2 \( mm \) h\(^{-1}\) to 1.0 \( mm \) h\(^{-1}\)). While for the threshold of 2.0 \( mm \) h\(^{-1}\), both schemes presented very low skills and the difference between POD\(_{\text{radar}}\) and POD\(_{\text{radar+rainsat}}\) was always less than 0.05, which proves that the adjustment led by the use of the “RainSat” analysis was limited in distinguishing relatively strong cells.

False Alarm Ratio (FAR) statistics (left-bottom) showed that the combined analysis could result higher false alarms especially for the first 3 h. After that, due to the rapidly increasing FAR for the radar alone scheme, the combined analysis became superior gradually.

More balanced scores, Equitable Threat Score (ETS), were also calculated (right-top) for taking into account false alarms, missed events and successfully forecast events together. It is apparent that for the first 0-3 hours, both schemes provided similar results. For the relatively small thresholds (less than 1.0 \( mm \) h\(^{-1}\)), the combined analysis provided higher skills while for the threshold greater than 1.0 \( mm \) h\(^{-1}\), the radar alone scheme resulted in slightly higher scores. After about 3 hours, the combined analysis outperformed the radar alone scheme, although the scores for both schemes were already very small.

Frequency Bias index (FBi) shows that both schemes underestimated the precipitation area corresponding to all thresholds. Overall, the combined analysis produced better rainfall estimates in precipitation over a total of 6 hours based on the FBi scores. For example, for the first 3 h, the combined analysis showed the FBi at about 0.97 on average while only 0.7-0.77 was presented by the radar alone scheme.

Generally, this case study showed that the use of the “RainSat” technique for the extrapolation based nowcasting could improve the precipitation estimates somewhat,
especially for the widespread and less intense rainfall. For relatively strong cells, the combined analysis might provide a slight improvement after 2-3 hours but due to the limited predictability, the skill of extrapolation based nowcasting was already very limited. However, a better 3-6 h precipitation forecasts with straightforward extrapolation method may still be important for the advanced NWP-nowcasting merged forecasting systems such as NIMROD, as the NWP-extrapolation weighting calculation is usually carried out up to 6 hours (although the weighting for extrapolation technique after 2-3 hours is usually very small).

4.5.2. Case 2: 07 January 2012
Case 2 presents another case study for investigating the adjustments resulting from the involvement of the “RainSat” analysis in nowcasting. From 06 to 07 January 2012, a wide rain band affected the North Island. Strong precipitation were observed by the radar at Bay of Plenty (POB) from about 2000 UTC 06 January and then the rain band moved southeastward, strengthened and moved out of the radar range after about 9 hours. In this case study, two successive images obtained at 2300 UTC 06 January and 0000 UTC 07 January from both the radar and the “RainSat” analysis were used to generate the extrapolation based forecasts for the next 6 hours.

It is worth noting that for this case, better results could be achieved in the BOP coverage area by using Auckland radar data. The selection of the BOP radar in this chapter is because that BOP radar, which contained information about the main rain band, could better serve our purpose for demonstration.

Figure 4.10 shows the successive images for the radar data, the “RainSat” analysis and the combined analysis for Case 2. As in Case 1, we find that the combined analysis has the capability of largely extending the availability of rainfall observations out of the radar range. The possible false alarms delineated by the “RainSat” analysis were also eliminated in the radar area by the combined analysis and therefore the motion vectors estimated by the combined analysis within the radar range were expected to have a higher correlation to the ones estimated by radar alone.

Figure 4.11 shows the associated motion vectors estimated for Case 2 according to the images obtained at 2300 UTC 06 January and 0000 UTC 07 January 2012. Apparently,
motion vectors were adjusted significantly by the involvement of “RainSat”. For example, in the Central North Island, the direction of motion vectors estimated by the radar alone scheme was more likely the northeast-southwest on average. In contrast, north vectors were presented in the region by the combined analysis. In addition, in the area near the edge of the radar range, a number of zero motion vectors were shown by the radar alone scheme while for the combined analysis, north-west vectors were given in general, which were closer to the visual evaluation of the associated radar images. In the area out of the radar range, reasonable motion vectors were estimated based on the “RainSat” analysis, which indicated that more precipitation might move into the radar range in next few hours or so.

Figure 4.12 shows the nowcasts generated by the radar alone and the combined analysis, and the associated radar observations. We find very significant adjustments were made by the additional “RainSat” analysis, especially after about 2-3 hours. For the lead time of (T+1), the radar based nowcast was very similar to the one provided by the combined analysis. The region from Hamilton to Tauranga was not affected by precipitation by the radar alone technique while moderate rainfall was presented by the combined analysis, which was more realistic compared to the associated radar observations. One hour later (T+2), there was no obvious movement appearing in the precipitation estimated by the radar alone scheme. While for the combined analysis, the main rain band moved southwestward and started bringing sufficient rainfall over the central North Island. Compared to the observation at (T+1), both forecasts from radar and ”radar+RainSat” provided relatively poorer skill on representing the rainfall patterns due to the limited capability of processing the echo splitting and merging for the cross-correlation approach. For the lead time of (T+3), the main rain band estimated by radar alone moved slightly towards north, while the rain band estimated from the combined analysis apparently moved southwestward and affected the New Plymouth region. Both estimates were not able to address the new developed echo affecting the east coast of the region from Coromandel to Gisborne.

Overall, we found that there were significant differences between the nowcasting made by the radar alone and the combined analysis. Compared to the associated observations, both schemes could not address the echo splitting/merging well, which means that the use of the “RainSat” technique with cross correlation tracking is still unable to improve the current skill of extrapolation based nowcasting fundamentally. However, it is apparent that the
combined analysis has the capability of providing more accurate precipitation distributions compared to the traditional radar alone scheme, especially after 1-2 hours.

The biases in reflectivity (dBZ) weighted echo centre and precipitation area for Case 2 were shown in Figure 4.13 and Figure 4.14, respectively. From Figure 4.13, it is evident that the bias increased rapidly for the radar alone scheme from about 43 km (1 h) to 95 km (6 h), while for the “radar+RainSat” analysis, the bias was relatively stable and increased slowly from about 38 km (1 h) to 55 km (6 h). It indicates that the combined analysis based extrapolation might generate more significant improvements for the nowcasting of uniform precipitation as the lead time increased. From Figure 4.14, we find that both schemes provided very high biases in estimated precipitation area corresponding to large underestimates. However, the one estimated by the combined analysis was smaller (although it was still greater than 300 km$^2$). It is apparent that the bias of echo area was not very sensitive to the changing forecast lead time for this case, especially for the radar alone scheme. The bias was fluctuated at 550 km$^2$ after 1 h (for the combined analysis scheme, the bias increased from 350 km$^2$ to about 400 km$^2$ from 1 to 3 h, then it decreased to the minimum of about 280 km$^2$ thereafter). The bias analysis could be explained by the associated visual evaluation shown in Figure 4.12: the radar based precipitation area estimates had not changed significantly during the first 3 hours, while the precipitation area from the combined analysis based nowcasting increased, which has higher correlation to the associated observations.

Figure 4.15 shows POD, ETS, FAR and FBi scores for Case 2 in terms of 6 hours extrapolation based forecasts. In contrast to the scores obtained for Case 1, the combined analysis provided higher POD and ETS, and lower FAR over the entire verification period. For example, for the threshold of 0.5 mm h$^{-1}$, POD$_{radar+RainSat}$ showed the scores ranged from 0.6 to 0.7, while POD$_{radar}$ scores were between 0.45 and 0.7, and the score decreased rapidly as the lead time increased. For the FBi statistics, compared to the combined analysis, precipitation was underestimated by the radar alone scheme on average, which was caused by the use of incomplete echoes at far range. However, it is still worth noting that, precipitation was also underestimated by the combined analysis scheme for the first 1-4 hours, especially for the relatively small and strong cells.
4.6 Discussions and Conclusion

In this chapter, we investigated the possibility of using satellite retrieved precipitation to improve the traditional radar alone based nowcasting in New Zealand, particularly to deal with tracking errors for extensive rain areas extending over the maximum radar range. Since the “RainSat” technique provides the rainfall estimates trained by radar, it is used to provide the supplement for the incomplete rain bands observed by radar alone. The cross-correlation technique is applied to advect both the radar retrieved rainfall and merged analysis.

From subjective evaluations, we found that motion vectors were adjusted well, especially in the area near the edge of the radar range. Moreover, the predicted rainfall patterns for the combined analysis were slightly better than the ones obtained from the traditional radar alone scheme, which can be explained by the bias statistics carried out for precipitation area and reflectivity weighted echo centre.

Forecast skill scores (POD, ETS, FAR and FBi) also showed that the merged analysis have the capability of providing higher skill in nowcasting compared to the radar alone scheme, especially after about 2-3 hours (although by then the skills for both schemes were already limited) when scored at high resolution.

Although there are many errors inherent in the “RainSat” analysis and the associated “radar+RainSat” based nowcasting, the use of the combined analysis is still expected to be useful for giving full delineation of rain bands. Consequently, it is also a relatively straightforward method to reduce the errors caused by the use of incomplete radar imaging for the nowcasting of extensive rainfall patterns.

However, it is worth noting that the “RainSat” technique is better at delineating precipitation area rather than estimating the rain rates. For the cross-correlation based extrapolation, the “Best fit” coefficient for the target extrapolation area is calculated based on the rainfall characteristics, which include both the pattern and intensity, of adjacent areas. Therefore, the errors inherent in the rainfall intensity estimates may lead to significant errors in the estimated motion vectors. In addition, poor skill in the rain rate estimates for the “RainSat” analysis also could lead to poor skill of estimating the
precipitation intensity for the subsequent hours (see Section 3.6).

In addition, problems for nowcasting, like the prediction of echo splitting and merging, will not be improved by the use of the "RainSat" analysis, since it just provides a way for providing relatively complete delineation of rain band and thus adjusting the estimates of motion vector and precipitation area. This chapter does not include the discussion of any new extrapolation techniques. The cross-correlation scheme is the only technique used here to investigate the “RainSat” leading adjustments. Any operational system would likely use more sophisticated tracking algorithms but it is believed that we have shown the potential of using satellite imagery to solve the tracking over the edge of radar coverage problem of nowcasting.
Chapter 5. The implementation of reverse Kessler warm rain scheme for radar reflectivity assimilation using a nudging approach in New Zealand

5.1 Abstract
Reverse Kessler warm rain processes were implemented within the Weather Research and Forecasting Model (WRF) and coupled with a Newtonian relaxation, or nudging technique designed to improve quantitative precipitation forecasting (QPF) in New Zealand by making use of observed radar reflectivity and modest computing facilities. One of the reasons for developing such a scheme, rather than using 4D-Var for example, is that radar VAR scheme in general, and 4D-Var in particular, requires computational resources beyond the capability of most university groups and indeed some national forecasting centres. The new scheme adjusts the model water vapour mixing ratio profiles based on observed reflectivity at each time step within an assimilation time window. The whole scheme can be divided into following steps: (i) The radar reflectivity is first converted to rain water, and (ii) then the rain water is used to derive cloud water content according to the reverse Kessler scheme; (iii) The cloud water content associated water vapour mixing ratio is then calculated based on the saturation adjustment processes; (iv) Finally the adjusted water vapour is nudged into the model to update the model background. 13 rainfall cases, which occurred in the summer of 2011/2012 in New Zealand, were used to evaluate the new scheme. Different forecast scores were calculated and showed that the new scheme was able to improve precipitation forecasts on average up to around 7 hours ahead depending on different verification thresholds.

5.2 Introduction
Quantitative precipitation forecasting (QPF) plays an important role in weather-related risk management. However, probably largely due to the inaccuracy of initial fields and the associated “spin-up” problem, QPF does not usually produce results of high accuracy. It is to be hoped that improved data assimilation will be able to improve initial backgrounds and thus significantly improve QPF on the short term scale. Weather radar networks, like the one operated in New Zealand by NZ MetService (Crouch, 2003), are able to provide very high spatial and temporal resolution rainfall observations and the availability of such data
allows the use of radar reflectivity and Doppler velocity to initialize models with better precipitation related fields.

There are various approaches for assimilating radar observation in NWP models for QPF. These approaches usually have different target variables to adjust, different effective periods and different computational resources demands. The variational (VAR) technique has been implemented to assimilate variety types of observations, including radar reflectivity and Doppler velocity (e.g., Barker et al., 2004; Huang et al., 2009; Barker et al., 2012). Encouraging results have shown that it can be effective to assimilate radar data for mesoscale NWP (e.g., Sun and Wang, 2013). However, there are several known issues for Variational based data assimilation (Dance, 2004; Caya and Snyder, 2005; Barker et al., 2012; Sokol, 2009; Sun 2005; Sun and Wang 2013; Sun et al., 2013; Wang et al., 2013b): (1) the unknown background error PDFs: the background error PDFs play several important roles in data assimilation, for example, spreading and smoothing information, however, it cannot always be estimated well. Statistical models like the NMC method have been applied. We all know that forecast differences are only a crude approximation to background error, there are several factors can contribute to the difference include the change in LBC, and also the impact of data assimilation for two forecasts, while for areas with sparse observations, the changes in initial conditions may be not large enough to estimate the full range of background errors. Also, systematic errors of the model cannot be accounted for. (2) Observation error is also one of the important error sources. According to the assumptions of Variational method, observation errors should not self-correlated or correlate to the model background. However, it is not always the case. For example, for radar data assimilation, the systematic error of a single radar can contribute to a range of observations, even with some data thinning techniques applied. For Doppler velocity assimilation, we may apply background check to address the ambiguity issue, however, it makes the model background and observation error correlated. (3) In Variational related data assimilation techniques, the selection of control variables may also contribute to the errors. First, we should assume the pdf for the variable is Gaussian, and uncorrelated to each other, which makes the B matrix diagonal while no choice of control variable can fully satisfy these requirements. (4) The use of flow dependent covariances is also an issue, especially for 3DVar, as the background error covariances are averaged over a long period (e.g., using NMC method). For 4DVar, the use of the perturbation forecast model throughout the assimilation window may help to address this problem. (5) Specifically for
3DVar, applying a temporal range of observations at one time could lead the representative error while for 4DVar, besides the errors we listed above, usually it is necessary to reduce the resolution to avoid the required expensive computational resources. A good summary of the errors inherent in the data assimilation can be found from Dance (2014). Moreover, in the 3D-Var direction radar data assimilation system of the current version of Weather Research and Forecasting model Data Assimilation System (WRFDA), the linearization error of the existing reflectivity assimilation operator may cause the difficulty in convergence of a cost function when the background rainwater is very small (Sun and Crook, 1997; Wang et al., 2013b).

The Ensemble Kalman Filter (EnKF) is another method, which has a demonstrated potential for incorporating radar data into models (Sun, 2005) and may require less computational resources compared to 4D-Var depending on the number of ensemble members and the DA resolution (e.g., Snyder and Zhang, 2003; Zhang et al., 2004). Caya et al. (2005) found that the EnKF scheme performed less well than 4D-Var in the first two cycles (by using 4D-Var Doppler Radar Analysis System (VDRAS) and simulated radar data) while these two techniques had comparable performance thereafter. From an operational viewpoint, the number of members for the EnKF must be limited, which influences the accuracy of the error characteristics and consequently the accuracy of the forecast would be compromised (Sokol and Zacharov, 2012).

An alternative simple technique - nudging, which is set up based on an algorithm in which the model is relaxed towards to observed values, presented the potential for assimilating radar observations at high resolution but with less computational cost (e.g., Stauffer and Seaman, 1990; Seaman and Stauffer, 1994; Stephan et al., 2008; Dixon et al., 2009). Nudging scheme is often carried out on the (very) short-range precipitation forecasting operationally because of the unaffordable computational demands from the 4D-Var and EnKF methods (Sokol and Zacharov, 2012). For precipitation nudging, a widely used scheme is the “latent heat” (LHN) method, which was first designed by Manobianco et al. (1994). Similar approaches have been developed and implemented in the UK Mesoscale Model, UK Unified Model (Jones and Macpherson, 1997) and the Bologna Limited Area Model (BOLAM) (Davolio and Buzzi, 2004). LHN rescales model latent heat profiles by the ratio of derived surface rain rates and model precipitation. It has been proven an effective method in improving precipitation forecasting for the first few hours. Another
alternative idea, which is usually referred as Physical Initialization (PI), was developed based on the assumption that updrafts associated with horizontal humidity flux convergence in the lower part of the cloudy column lead to rain formation. This scheme was first investigated in tropical regions (Krishnamurti et al., 1991), both the satellite observed rainfall rates and vertically integrated radiative heating rates were used to diagnose the surface fluxes of water vapour and sensible heat, and a reverse cumulus parameterization algorithm was employed to analyse the humidity related variables according to the imposed precipitation rates. Outgoing longwave radiation (OLR) matching process was used to improve the model cloud cover distributions. Similar algorithms were developed and implemented by Nunes and Cocke (2004) in a regional spectral model over South America. For radar reflectivity PI, Haase et al. (2000) developed a method (Physical Initialization Bonn (PIB)) for adjusting the model vertical wind by a simplified precipitation mechanism. Specific water vapour and cloud water are determined by the pre-defined vertical distributions of cloud properties. (In this scheme, the cloud top is estimated from satellite or using 3D radar observation (Yang et al., 2006) and cloud base height is set to lifting condensation level (LCL) derived from synoptic observation). Compared to the methods mentioned above, Water Vapour Correction (WVC) method is another simple and effective reflectivity assimilation approach developed by Sokol and Zacharov (2012). It is easier to be set up, but it introduces more empirical statistics and configurations. During the Mesoscale Alpine Programme (MAP) (Hagen and Yuter, 2003), this method was tested in the COSMO model (Stephan et al., 2008) in Czech Republic (CR) and the results showed that the WVC method was able to improve the local forecasts of precipitation significantly for the first several hours. Detailed information about this algorithm can be found in Section 7.3.2.

For assimilating radar reflectivity observation in WRF with modest computational resources, this chapter describes an alternative method for radar assimilation other than the WRF VAR direct radar assimilation. The new scheme is inspired by the WVC technique and the idea of Krishnamurti et al. (1991), and it is developed based on reversing the Kessler warm rain processes (RK-nudging) (Kessler, 1969). The principle of this method is similar to the LHN and WVC approaches, which are standard options for some operational model systems like the Unified Model (UM) and COSMO model, as the precipitation is increased or decreased by adding (removing) water vapour flux into (from) the model backgrounds. The adjustment (releasing/absorbing) of heat could be caused by
oversaturation or undersaturation after the corrections of water vapour and then, at subsequent model integration steps, the corresponding phase changes and relevant effects on the heat balance may be applied.

In the LHN method, the potential temperature increments are based on a scaling of the profiles of $R_{\text{obs}} / R_{\text{bk}}$, where $R_{\text{obs}}$ and $R_{\text{bk}}$ indicate the observed rain rate and the model background (or “first guess”) rain rate, respectively. It is apparent that this relationship is not valid when the background is “dry” ($R_{\text{bk}} = 0$). One approach to address this issue is to “borrow” the moisture-related fields from the nearest “wet” grid point, but clearly it might introduce significant uncertainties, especially when we try to trigger isolated cell which is far away from the main rain band. Therefore, the contrast to the LHN method, the new scheme can be implemented in the “dry” model background though a physical rather than mathematical argument. Moreover, in contrast to the radar reflectivity PI approach, the RK-nudging scheme has the capability of processing 3D radar volume scanning information without the estimation of cloud distributions (e.g., cloud top and bottom height) before the assimilation using other types of observations (e.g., satellite and synoptic observations). In addition, the new approach, which is set up based on the well tested Kessler warm rain scheme, does not require the coefficients which have to be determined over a large number of cases studies as is necessary in the WVC approach. Thus, the RK-nudging method has the potential to be straightforwardly implemented in different regions.

5.3 The RK-Nudging assimilation scheme

“Warm rain” refers to rain derived from clouds without ice-phase processes. Warm rain can be considered as a relatively simple, but integral component of a precipitation system (e.g., Lau and Wu, 2003) as it is capable of effectively adjusting moistening and heating in a convection system. The Kessler scheme (Kessler, 1969) presents a very simple warm rain parameterization which is still widely used today (e.g., Ogura and Takahas, 1973; Dudhia, 1989; Schultz, 1995; Wang et al., 2012). In this chapter, the Kessler scheme has been reversed (RK) in order to adjust the model profile of water vapour mixing ratio according to observed radar reflectivity. In the RK-nudging scheme, the increments of rain water mixing ratio between radar derivations and model backgrounds are assumed to be entirely resulted from the autoconversion, accretion and evaporation processes. Most moisture related states, except rain water, cloud water and water vapour, are adjusted freely by the
Chapter 5. The implementation of reverse Kessler warm rain scheme for radar reflectivity assimilation using a nudging approach in New Zealand

model dynamical and physical processes according to the adjusted water vapour. The orographic effects, which present in most regions of New Zealand, especially in the South Island, can provide the forced upward motion for the RK scheme after the saturation adjustment. There are mainly four steps to implement the RK nudging scheme into model:

(i) First, the rain water mixing ratio associated with radar observed reflectivity is determined according to the reversed $Z - q_r$ relationship:

$$q_{r, \text{radar}} = \frac{1}{\rho} \cdot 10^{\frac{Z - c_1}{c_2}}$$

Where $Z$ is the reflectivity in dBZ, $\rho$ is the air density and $q_{r, \text{radar}}$ indicates the rain water mixing ratio derived from radar. Under the assumption that the relation between $Z$ and $q_{r, \text{radar}}$ is set up based on the Marshal-Palmer distribution of raindrop size, $c_1$ and $c_2$ can be constant values of 43.1 and 17.5, respectively (Sun and Crook, 1997). This equation is also employed as the nonlinear observation operator $H$ for WRF 3DVar direct radar reflectivity assimilation system, and the performance of $H$ has been investigated in detail by Wang et al. (2013).

(ii) The difference between model rain water and radar derived rain water can be represented as:

$$\Delta q_r = q_{r, \text{radar}} - q_r$$

Therefore, if $\Delta q_r > 0$ (the model rain water is underestimated), we assumed that the increments of rain water are entirely defined by the increments of cloud water, thus following equation can be symbolically used to approximate the $\Delta q_r$ producing processes:

$$\Delta q_r = A_r (\Delta q_c) + C_r (q_r, \Delta q_c) - E_r$$

Where $A_r$, $C_r$ and $E_r$ represent autoconversion, accretion and evaporation, respectively. $q_r$ and $q_v$ are model rain water and water vapour mixing ratio. $\Delta q_c$ is the changes of cloud water leading the rain water adjustments. The different terms of above equation can be given by (Kessler, 1969; Klemp and Wilhelmson, 1978):

$$A_r (\Delta q_c) = k_1 (\Delta q_c - a)$$

$$C_r (\Delta q_c, q_r) = k_2 (\Delta q_c) q_r^c$$
Chapter 5. The implementation of reverse Kessler warm rain scheme for radar reflectivity assimilation using a nudging approach in New Zealand

\[ E_r = \frac{1}{\rho} \frac{C(1-q_v/s_e)(\bar{\rho}q_r)^{0.525}}{5.4 \times 10^5 + 2.55 \times 10^5/pq_{vs}} \]  

(5.6)

Where \( k_1 \), \( k_2 \) and \( a \) are all constants. In this paper they have been selected as: \( k_1 = 0.001 \text{s}^{-1} \), \( k_2 = 2.2 \text{s}^{-1} \) and \( a = 0.001 \text{ g g}^{-1} \). \( C \) is the ventilation factor. Thus, based on the equations from 5.3 to 5.6, the increments of cloud water can be simply represented as:

\[ \Delta q_c = \max\left[\frac{\Delta q_r + k_1 a + E_r}{k_1 + k_2 q_r^*}, 0.0\right] \]  

(5.7)

(iii) The conversion between cloud water and water vapour in this paper is defined by the saturation adjustment described by Soong and Ogura (1973) and Klemp and Wilhelmson (1978). This process is briefly given here: the dummy values which only taking into account the dynamical terms in the model prognostic equations for water vapour and saturation mixing ratio are represented by \( q_v^* \) and \( q_{vs}^* \), respectively. If \( q_v^* > q_{vs}^* \), the air is supersaturated while it is not permitted in the model. Thus, water vapour is adjusted to

\[ q_v = q_v^* - r(q_v^* - q_{vs}^*) \quad \text{with} \quad r = \left[1 + \frac{237a \pi q_{vs}^*}{\left(\pi \theta^* - 36\right)^2 C_p \pi'}\right]^{-1}. \]

Considering the conservation equation \( q_v + q_c = q_v^* + q_c^* \) (Klemp and Wilhelmson, 1978), therefore we have

\[ q_c^* - r(q_v^* - q_{vs}^*) = q_v^* + q_c^* - q_c \quad \text{or} \quad r(q_v^* - q_{vs}^*) = q_c^* - q_c, \]

then \( q_c^* = \frac{q_c - q_c^*}{r} + q_{vs}^* \) can be derived.

Here we assume that \( q_v^* = q_v + \Delta q_v \) (also \( q_c^* = q_c + \Delta q_c \)), the increments of water vapour in the RK-nudging therefore can be written as:

\[ \Delta q_v = \max\left(\frac{\Delta q_c}{r} - q_v + q_{vs}, 0.0\right) \]  

(5.8)

Where \( \pi_c \) is the non-dimensional pressure, \( a = 17.2694 \) and \( \theta^* \) is the potential temperature before the adjustment. In \( \pi = \pi_c + \Delta \pi / 2 \), \( \Delta \pi \) is the non-dimensional pressure difference between two levels that the air is in the moist adiabatic process.

If \( \Delta q_r < 0 \) (the model rain water is overestimated), \( q_c \) and \( q_v \) can be addressed using a similar form of Equation (5.7) – (5.8), the only different is to keep \( q_c \) and \( q_v \) less than (or at least equal to) zero in the nudging processes.
\[ \Delta q_c = \min[\Delta q_r + k_r a + E_r(q_r^c - q_r), 0.0] \]
\[ \Delta q_v = \min(\frac{\Delta q_c}{r} - q_v + q_{\text{ns}}, 0.0) \]

(iv) At the last step, \( \Delta q_v \) is used to adjust the model background water vapour mixing ratio using the WRF Obs-nudging system (Liu et al., 2005). The nudging factor was selected to \( 3 \times 10^{-4} \) s\(^{-1} \) for all cases in order to keep the model stable and still give the priority to the model physical and dynamical processes during the forward integration processes (Stauffer and Seaman, 1990). The horizontal influential radius was given to 3.0 km, which is equal to the model spatial resolution. This was helpful to make the effects of assimilation not to be too widespread and each grid point can be determined largely by the most closely adjacent observed value. Considering that we just made a one-time nudging and no phase error was considered, a short temporal influential radius was set (30 min).

5.4 Results

In this section, the evaluations of the assimilation scheme with a selection of 13 cases were drawn from the summer of 2011/2012 (between November 2011 and January 2012). Synoptic analyses (not shown) indicate that either most of these events resulted from moist air masses developing in the Tasman Sea or they were generated locally by the orographic impacts of South Alps, which mean that these 13 cases have covered most common precipitation generation mechanisms that occur during a NZ summer. The daily accumulated rainfall observed by NZ National Institute of Water and Atmosphere Research (NIWA) / MetService of these 13 cases are given in Chapter 2 (Table 2.2).

All cases were initialized using previous 3 h free forecasts from WRF. The reason we selected the initialization after 3 hours is because we want to make the experimental environment as close as possible to a 3 hours cycling system but also considering the limitation of our current computational resources. From the surface pressure tendency statistics, the spin-up period might last up to 6 hours (figure now shown), so our experiments were expected to show how the precipitation forecasts can be improved for a very short range period while the moderate imbalance still exists in the model background. (It is worth noting that, currently, synoptic observations are assimilated into the MetService
Chapter 5. The implementation of reverse Kessler warm rain scheme for radar reflectivity assimilation using a nudging approach in New Zealand

NWP model operationally, thus, the results shown in this study, which with only radar reflectivity assimilated, may be different from the expected one obtained from any operational applications. Observed reflectivity from the NZ MetService radars was incorporated for the “DA” runs (see Figure 5.1). In this chapter, we did not update the backgrounds continuously since the main purpose of this chapter is to investigate the “immediate” response of WRF from the one-time RK-nudging scheme process, and also, our computational resources did not support the incorporation of massive observations continuously into the model at high resolution. Another reason why we did not incorporate the observations throughout the model spin-up period is because from Wang et al., (2013), in order to use a simple liquid only reflectivity assimilation scheme in the model with less errors, the time window should be short enough. In this thesis, we adopted 30 minutes as our DA window. Overall, we simply assume that, the improvement from a “one-time” nudging test is a precondition to the further implementation of a comprehensive system at the next step.

The errors associated with phase changes were not considered in this chapter, but it is worthwhile to mention that, within the 30 min of assimilation window, there might be significant changes in the precipitation distribution and intensity. For example, in Figure 5.2, the precipitation located in the west coast of New Plymouth was strengthened from (T+0) to (T+30min). Errors might be caused if we use the (T+0) observed reflectivity to represent the characteristics of precipitation over the entire 30 min.

The model was configured with two domains (Figure 5.3), the outer domain (D01) covers the Tasman Sea with the horizontal grid resolution of 9 km (it comes with the same domain as the selected area for our satellite based analysis shown in last chapters), and the inner domain (D02) covers New Zealand and the surrounding waters at 3 km grid spacing. The model physics options adopted in this chapter includes: the Kessler scheme was adopted for microphysics processes. Other parameterizations used include the Rapid Radiative Transfer Model (RRTM) scheme (Mlawer et al., 1997) for long wave radiation and the Dudhia scheme (Dudhia, 1989) for short wave radiation, the Yonsei University (YSU) scheme (Noh et al., 2003) for planetary boundary layer parameterization. NCEP Final Operational Global Analysis data (FNL) were used as both the initial conditions and boundary conditions. FNL data come from the Global data assimilation system, which continuously collects observations data from the Global Telecommunications System
(GTS). Compared to data from Global Forecast System (GFS), the FNLs are made with the same model, but are prepared about an hour after GFS is initialized. Therefore it actually comes with a more comprehensive data assimilation process with more observations are assimilated. In order to simplify our experiments, and also save some computational resources, we did not re-assimilate the conventional observations in the model. The verifications between model forecasts and observations started from (T+1). One hour model rainfall accumulations were verified against one hour radar derived rainfall accumulations (radar data were spatially averaged to 3 km) in terms of different thresholds. The hourly radar rainfall accumulations were calibrated with local rain gauges using an advection based interpolation scheme (Heistermann et al., 2013; Fabry et al., 1994; Shucksmith et al., 2011).

The forecasts were evaluated using both point wise and fuzzy verification schemes in the region covered by radars. First, Equitable Threat Score (ETS) and False Alarm Ratio (FAR) were calculated by comparing radar observations and forecasts point by point. Second, a fuzzy verification method, Fractions Skill Score (FSS) (Roberts and Lean, 2008) is used. FSS is well suitable for discontinuous fields (e.g., precipitation) and can be used to compare forecasts at different spatial scales. FSS ranges between 0 (completely wrong forecast) and 1 (perfect forecast).

It is worth noting that all of these scores are largely determined by given thresholds, and it is difficult to determine if a forecast was useful by using any types of objective skill scores. However, these scores provide an easy way to compare the relative skill of different forecast approaches or the capability of same forecast scheme over a certain period (Rossa et al., 2008; Gilleland et al., 2010).

Scores were combined over all selected cases in terms of different thresholds (0.5 mm h$^{-1}$, 1.0 mm h$^{-1}$, 2.0 mm h$^{-1}$ and 5.0 mm h$^{-1}$) and shown in Figure 5.4 (ETS statistics), Figure 5.5 (FAR statistics) and Figure 5.6 (FSS statistics corresponding to different verification scales). From these three figures, we can clearly see that the RK-nudging scheme was able to improve the precipitation forecasting significantly, especially for the first 2 hours. When the threshold was set to above 2.0 mm h$^{-1}$, the forecast skills for both the CTL and DA experiments were very low, which means that the assimilation scheme was still not capable
of capturing relatively intense precipitation. The impacts of assimilation reduced gradually with the lead hours increased, the positive effects led by the RK-nudging could endure up to around 7 hours (by ETS and FAR) and 6 hours (by FSS). After that, the difference between the CTL runs and DA runs were not obvious.

From the FAR scores, we can easily find that when the threshold was set to 5.0 mm h^{-1}, the assimilation increased the false alarm ratio during the first few hours. There are several plausible reasons for that, it might be, perhaps, that there was spurious high intensity precipitation wrongly produced by the assimilation, and when using skill scores to evaluate the forecasts, the wrong precipitation prediction introduced by the nudging processes could not be offset by its ability of reducing false warnings in other places when the threshold became high. Also, the imperfect radar data quality (e.g., ground clutter, the effects from the bright band etc.) might also contribute to the uncertainties to the skill scores we showed here.

It is worthwhile to note that, from all above statistical scores, the skills of the DA runs followed the similar trend as the CTL runs. For example, high CTL based scores are usually associated with high Da based scores and poor CTL forecasts came with poor performance of the assimilation experiments as well. This indicates that even when the precipitation observations have been incorporated into the model using the RK-nudging scheme, the forecast skills were still largely determined by the model dynamical and physical processes and simulated large scale features. Figure 5.7 gives the difference between the manually produced Mean Sea Level Pressure (MSLP) analysis obtained from the Bureau of Meteorology, Australia and the associated WRF simulated MSLP analysis. It is obvious that the WRF simulated low pressure centre (LPC) located to the southwest of the manually analysed one, which could result the wrong simulated location of the main precipitation band. Apparently, the water vapour adjustment in this case was not enough to correct the pressure system sufficiently and subsequently made significant changes to the precipitation development. The results are similar to Sokol and Zacharov (2012), which suggested that sometimes the nudging based radar reflectivity assimilation alone is too weak to adjust the state of the model variables then the development of convective activity cannot be supported. In such case, the assimilation of satellite data or wind fields may provide more fundamental impacts on the predicted precipitation development.
Subjective assessments of each case were carried out and the results showed that the RK-nudging could give considerable benefit in increasing precipitation areas in accord with radar observations, while it has only slight improvements on reducing false precipitation warnings. One possible reason is because of the relatively high threshold (15 dBZ) applied to the radar data for the assimilation experiments. Uncertainties inherent in the algorithm itself may also contribute to this phenomena. From equation 5.7 and 5.9, it is clear that if $\Delta q_e < 0$, it is more difficult to guarantee that $\Delta q_e$ would be smaller than zero as well. We present an example of subjective examination for the case of 1 November 2011 (Figure 5.8). From 31 October to 2 November 2011, isolated rain bands developed over the Tasman Sea and affected New Zealand. Resulting heavy rainfall led to numerous hazards like flooding and landslides across the country, especially in the North Island. The radars operated by NZ MetService detected strong echoes from around 2100-2300 UTC 31 October, and then the echoes moved eastward rapidly and passed out of the radar range after about 18 hours. The maximum reported reflectivity was recorded in some regions (e.g., Bay of Plenty) in the North Island and the top of the South Island (from Picton to Nelson region).

Figure 5.8 gives the comparisons from 0400 UTC (30 minutes after the end of assimilation time window) between the forecasts and observations. The results without (CTL) and with (DA) radar adjustments are shown at the left and middle column, respectively. Associated radar observations are shown at the right column.

At 0400 UTC, CTL did not predict the precipitation in the Nelson/Tasman region at all while DA showed the rain band well in this region but with higher estimated intensity in general. There were isolated light - moderate rainfalls observed in the central of the North Island where neither experiment provided very good simulations. Additional rainfall areas predicted by both the CTL and DA runs in the bottom of the South Island. However, it is hard to say whether the simulations were correct or not as the blocking of radar detection in this area made us being unable to tell the truth. Overall, DA run showed much higher capability to forecast the rainfall distributions compared to CTL, but both experiments overestimated the intensity of rainfall in most places.
One hour later (0500 UTC), similar to 0400 UTC, the main rain bands simulated by CTL were still located in the west of NZ and had almost no impact on the North Island except the Northland region. The CTL run was still not able to produce precipitation in the Nelson/Tasman region although approximately 5.0 mm h\(^{-1}\) rainfalls were already presented in the observations. In contrast, the DA run produced an isolated rain cell along the west coast of the North Island and there were rainfalls presented at the top of the South Island (Nelson/Tasman region). However, similar to the CTL run, the main rain band simulated by DA was still located in the west of the North Island.

The difference between the DA and CTL runs decreased as the forecast lead time increased. At 0600 UTC (3 hours after the end of assimilation), both experiments failed to provide satisfactory predictions in the North Island. Spurious echoes were produced by both experiments in the Central South Island. However, compared to the observations, the DA run provided better simulations in the Tasman region. Moreover, the forecasts by DA were more realistic in the top of the North Island compared to the CTL run.

At 0700 UTC (not shown), the CTL and DA runs provided very similar results in the North Island. However, DA presented a border precipitation area in the region of New Plymouth, which is more realistic compared to the corresponding CTL. Moreover, the rain band affected the South Island already moved across Picton and the DA run provided better forecasts in the region.

Figure 5.9 shows the vertical cross section (the position of the vertical cross-section is shown in Figure 5.8) of the simulated rain water (shaded) and vertical winds (solid contour). It is apparent that, from (172.00, -39.00) to (172.48, -40.12), where precipitation is mostly over the sea, the vertical winds have been adjusted by the model physical and dynamical prognostic formulae after the assimilation processes by adding/removing water vapour. In contrast, updraft and rain water also can be strengthened by topography as in the position from (173.2, -41.8) to (173.44, -42.36), where is the north section of the South Alps. Overall, the combination of the adjusted water vapour and topography would lead to the adjusted updraft, which could have significant effects on the moisture related fields development in the area of interest.
Generally, for the event of 1 November 2011, the DA run, which with the assimilation of observed reflectivity, was able to provide higher forecast skills on average compared to CTL by subjective evaluation. However, compared to the associated observations, both experiments (CTL and DA) overestimated the maximum intensity of rainfall significantly at the beginning although with the lead time increased, the simulated intensity became more reasonable. Moreover, the accumulated rainfall patterns were not improved apparently as the main simulated rain band from the DA run was still located at the west side of the corresponding observations on average, especially after 1-2 hours. This shows that the assimilation of wind fields from Doppler velocity might provide much better precipitation forecasts for this case. It is worthwhile to mention that, in WRF, there are no linear approximation errors existing in the WRF 3DVar Doppler velocity assimilation system, thus, by using the WRF direct radar assimilation system, the winds assimilation, in most cases, is capable of providing more positive effects compared to the 3DVar assimilation of reflectivity data (e.g., Xiao et al., 2005).

Figure 5.10 gives the statistics of maximum rain water mixing ratio (calculated from the column bottom to top at each grid point within the radar coverage) distributions at (T+1), which was 30 minutes after the end of the nudging time window. Horizontal and vertical axes indicate the values from the CTL run and DA run, respectively, for the case of 01 November 2011. It is obvious that, regardless of whether higher or lower values were assimilated, the nudging scheme and the model physical and dynamical processes might drive the expected result the opposite way: for example, the assimilation of lower radar derived rain water value (compared to the model backgrounds) could result higher output after the assimilation processes. However, for most grid points, when the higher (lower) value was assimilated to a relatively dryer (wetter) grid point, the model background value could be increased (decreased) accordingly. Moreover, from this figure, the performance of the RK-nudging on increasing rain water was clearly better than the capability of decreasing rain water, which was agreement with the subjective evaluations for most other cases selected in this chapter.

The comparisons between $\Delta q_r$ and the corresponding $\Delta q_r$ for the event before the nudging processes are shown in Figure 5.11. Apparently, for both the situations that $\Delta q_r > 0$ (observed rain water is larger than the model rain water) and $\Delta q_r < 0$ (observed rain water...
is less than the model rain water), the RK process was capable of responding appropriate on average. For $\Delta q_r > 0$, the associated $\Delta q_v$ is usually larger than zero and thus the model water vapour is expected to be increased by the subsequent nudging processes. In contrast, when $\Delta q_r < 0$, the model water vapour is expected to be decreased accordingly. It is obvious that the scheme does not provide a proportional relationship between $\Delta q_v$ and $\Delta q_r$. For example, for $\Delta q_r > 0$, when the rain water increments were $0.5 \times 10^{-4}$ kg kg$^{-1}$, the corresponding water vapour increments were approximately $1.0 \times 10^{-4}$ kg kg$^{-1}$ on average, while for $\Delta q_r < 0$, the water vapour decreased by around $0.5 \times 10^{-3}$ kg kg$^{-1}$ corresponding to the $-0.5 \times 10^{-4}$ kg kg$^{-1}$ of rain water increments. Moreover, if there is no minimization operator used in Equation 5.10, the scheme might provide increased water vapour increments even when the negative rain water increments were given, which shows that the model background fields might not be well in agreement with the reverse Kessler scheme at all grid points.

The WRF simulated maximum rain water in a volume for the DA run, CTL run and the associated radar derived rain water at 0400 UTC (30 min after the time window) were also presented in Figure 5.12. The relationship between radar observed reflectivity and rain water is given by Equation 5.1. It is apparent that, compared to the CTL run, the rain water produced by the DA run was closer to the actual observation, although both simulations missed several observed rain water in the west coast of the North Island.

5.5 Discussions

Considering the computing resources available for research applications in New Zealand, we conclude they are inadequate for 4D-Var radar assimilation now. The RK-nudging scheme was not only capable of providing better precipitation related backgrounds, but also required less computational resources relative to VAR and EnKF based approaches. It makes the RK-nudging scheme an effective method showing the potential to be used in a rapid update system.

Although the improvements produced by the RK-nudging scheme are scored by both subjective and objective evaluation schemes in the selected events, it is still necessary to mention the potential limitations of the scheme. One of the most potentially serious
limitations of the RK-nudging scheme comes from the use of the simple Kessler warm rain scheme, which is a liquid only scheme and does not include ice-phase changes (There are no cases selected in this chapter which an be considered as proceeding by wain rain processes alone). This issue becomes more significant as the time window increases, as Wang et al. (2013a) showed that a simple liquid only microphysics scheme is an acceptable substitute for the more complex, multi-phases ones only if the time window is short enough (e.g., less than 1 hour). Nevertheless, it is still worth noting that, the essential feature of the Kessler scheme is that it simply separates liquid into cloud water and rainwater based on the Marshall-Palmer distribution for rain. For heavy rainfall which is produced by cold cloud processes, even when we adopt the time window less than 1 hour, the use of a warm rain processes in data assimilation may still well lead to uncertainties in the production of the “correct” partition increments. However, considering the complexity of the inclusion of ice-particle microphysics into model, currently the reflectivity based operators have been still developed according to the liquid only scheme for most data assimilation systems (e.g., Wang et al., 2013a; Sun and Wang, 2013).

On the other hand, even we assume that the use of simple liquid based scheme is acceptable, the empirical relationship based Kessler warm rain precipitation scheme still has significant errors (e.g., Seifert and Beheng, 2001; Rognvaldsson, 2013). Moreover, oversaturation is not allowed in the RK-nudging scheme and this could cause precipitation to be overestimated compared to the associated observation. Thus, a more complicated and accurate microphysics scheme is expected to be employed in radar reflectivity data assimilation in the future.

It is worth noting that, in this chapter, there are 13 cases involved in the assimilation experiments, and the precipitation forecasts of most of the cases were improved by the RK-nudging method, but it is still not able to provide a full evaluation of the RK-nudging scheme over all synoptic characteristics, precipitation features and model backgrounds. A longer period of evaluation (1-3 years) is expected to be carried out in the future when stable computational resources are available.

### 5.6 Conclusion

This chapter described a simple approach, RK-nudging, for incorporating radar reflectivity
into WRF whilst avoiding expensive computational resources, which is essential in New Zealand or other similar countries that are using WRF but will not have very large high performance computer (HPC) in the near future. In the RK-nudging scheme, by the use of the reversed Kessler warm rain scheme and the associated saturation adjustments, the radar rainfall estimates can be assimilated into WRF: Reflectivity derived rain water is converted to the associated water vapour and then the nudging approach is used to assimilate the water vapour and adjust the model moisture fields accordingly. This approach can be easily implemented and it does not require large computational resources.

A total of 13 cases occurred in the 2011/2012 summer of New Zealand have been employed to investigate the RK-nudging scheme. Reflectivity observed by NZ MetService radars was incorporated into the model and the model was initialized with previous 3 h free forecasts. Different forecast skill scores (ETS, FAR and FSS) were used to show the skill changes resulting from the assimilation processes. The results showed that, the RK-nudging scheme was able to improve the forecasts on average up to several hours depending on the verification threshold set (e.g., from FSS, 5 hours for the threshold of 5.0 mm h$^{-1}$ and 6 hours for the threshold of 0.5 mm h$^{-1}$). However, the improvements produced by the nudging processes decreased rapidly with the verification threshold or forecast lead hours increased. An example of subjective examination for the case of 1 November 2011 was presented and the results showed that the RK-nudging scheme was capable of adjusting moisture and thus promoting the precipitation forecasting in the radar covered regions on average. In this case, the RK-nudging was able to provide better adjustments in predicting rainfall location rather than the intensity. The improvements resulting from the assimilation in this case also decreased with the lead hours increased, and after about 6 hours the improvements introduced by the assimilation became trivial.

In order to develop effective and economic radar reflectivity assimilation scheme(s) for New Zealand, the RK-nudging scheme is expected to be implemented together with other reflectivity nudging approaches (e.g., WVC technique) in WRF. Depending on the availability of computational resources, the comparisons between nudging and the more advanced WRF 4D-Var approach (Wang et al., 2013a; Sun and Wang, 2013) may be also worthwhile to be tried in the future.
Chapter 6. The application of the RK-nudging approach with different microphysics schemes in the model

6.1 Abstract
A nudging scheme was developed based on the Kessler warm rain processes in a reverse order (RK-nudging) for incorporating radar or satellite retrieved rain rates into model. The investigation of the RK-nudging approach showed that the improvements led by the assimilation of radar reflectivity could last up to about 7 hours on average in New Zealand. However, the use of other (usually more complicated) cloud physics schemes in model may introduce uncertainties in estimating rain water from the Kessler based RK-nudging adjusted water vapour. In order to implement the RK-nudging at the next step with a more complicated cloud physics configuration, sensitivity studies of the RK-nudging scheme with different cloud physics options in the model are essential. In this chapter, six microphysics schemes implemented in WRF have been tested with the RK-nudging approach. The results showed that the assimilation of radar retrieved rain rates could lead to moderate adjustment in temperature simulation while there were almost no effects on the correction of wind fields. For precipitation simulation, seems that the WRF Lin scheme showed the relatively higher skills on average with the RK-nudging approach, while the Kessler scheme provided the least. The results indicated that long term studies are required before the possible operational implementation for the RK-nudging data assimilation approach.

6.2 Introduction
New Zealand is expected to implement a clouds/precipitation data assimilation system for (very) short range precipitation forecasting in the near future. In order to initialize the NWP model with high resolution radar data and the "RainSat" analysis (Bellon et al.,1980; Bellon and Austin, 1978) in New Zealand with modest computational resources, a rain rate nudging scheme was developed (see Chapter 5) based on the Kessler warm rain scheme (Kessler, 1969) in a reverse order (RK-nudging) and the associated saturation adjustment. Case studies showed that the RK-nudging approach has the capability of adjusting the model background water vapour appropriately according to the assimilated observations. The improvements led by the assimilation could last up to 7-9 hours on average. The statistics also showed that the RK-nudging scheme might overestimate rain rates in some
cases mainly because (1) the cloud physics scheme used in the assimilation method is a liquid only scheme (apparently it is not the case in most actual precipitation systems) and (2) the assumption that oversaturation is not allowed during the nudging processes.

Apparently, the use of the simple liquid only Kessler scheme (and the associated saturation adjustment) to retrieve water vapour in the nudging algorithm may yield considerable uncertainties, especially when a mixed-phase scheme is applied to diagnose the clouds/precipitation fields during the nudging processes. In order to investigate such uncertainties, in this chapter, the RK-nudging method is applied to incorporate radar observed reflectivity into the Weather Research and Forecasting (WRF) model with six different configurations of model microphysics schemes: Kessler scheme (Kessler, 1969), Lin et al. scheme (Lin et al., 1983), WRF Single-Moment 3- class, 5-class and 6-class schemes (Hong et al., 2004 ; Hong and Lim, 2006) and the Eta microphysics scheme (Rogers et al., 2001). Those schemes have different computational resources demands, different number/types of variables considered and some of them are well tested in current operational models (e.g., the Eta scheme is applied at NCEP operationally). Obviously, different model microphysics schemes may be able to yield significant differences in the estimated moisture and related fields, even when they start the clouds/moisture diagnosis from the same RK-nudging adjusted water vapour. For example, Cossu and Hocke (2013) indicated that the Kessler scheme might provide the cloud liquid water up to 14 times greater than other schemes, while for other schemes, they still differed up to 79% in water vapour, 10 times in hydrometeors and 64% in accumulated precipitation in the selected cases. Therefore, the selection of the microphysics scheme can have essential impacts on the analysis of the water cycle during the nudging processes.

It is worth noting that, in data assimilation, considering the complexity of the inclusion of ice-particle microphysics into the model (e.g., a great variety of particle sizes and shapes), currently the radar reflectivity based operator for most data assimilation systems are still developed according to a liquid only scheme. Wang et al. (2013a) indicated that for the situation that the assimilation time window is short enough (e.g., less than 1 hour), a simple liquid only microphysics scheme is an acceptable substitute for the more complex, multi-phases approaches. In addition, considering that the characteristics of different rainfall events are usually unique, the development of a perfect microphysics scheme, which is suitable for all weather systems, is not expected to be done in the near future. Therefore,
the cloud physics resulted errors inherent in the reflectivity data assimilation, regardless of whether the assimilation method is developed based on a liquid only or multi-phases scheme, will always exist. It is apparent that these errors may be amplified, reduced or accumulated when the microphysics schemes adopted in the nudging system and that in the model forward integration processes are inconsistent.

In this chapter, different schemes were applied to investigate the surface temperature, surface winds and precipitation simulated from WRF after the time window of the RK-nudging adjustment. Methodology is given in Section 6.3, followed by the analysis of simulated results (Section 6.4). Section 6.5 gives discussion and conclusions.

6.3 Methodology

The RK-nudging method is developed based on the reverse Kessler warm rain processes (for retrieving cloud water from rain water) and the associated saturation adjustments (for calculating water vapour from the corresponding estimated cloud water). The detailed illustration of the RK-nudging method is given in Chapter 5. Here we only give an overall description of the scheme. First, the rain rates derived from rain gauges, radar reflectivity or other types of observations are used to calculate the corresponding cloud water increments $\Delta q_c$. Then we assume that the moisture is conservative during certain time steps and oversaturation is not allowed in the model, $\Delta q_c$ is converted to the increments of water vapour $\Delta q_v$ according to the saturation adjustments described by Soong and Ogura (1973) and Klemp and Wilhelmson (1978). The calculated $\Delta q_v$ is then compared to the model background water vapour and the final analysis is nudged into the model to adjust the related model background fields. At the subsequent time steps, the adjusted water vapour is applied to diagnose precipitation related fields (e.g., cloud and rain water) according to the usual formulations of the Kessler warm rain scheme, or other adopted microphysics schemes in the model.

In Chapter 5, the Kessler scheme was applied in WRF in order to remain consistent with the microphysics scheme used in the nudging processes. However, as we discussed before, the errors inherent in the Kessler scheme and other physical and dynamical processes may also affect such homogeneity, which means that the selection of other microphysics schemes has the possibility of yielding positive effects on the final analysis for the WRF.
simulations as they may be able to present more accurate estimates in moisture fields. In this chapter, we investigated the skills of the RK-nudging method on simulating surface temperature, winds and accumulated precipitation with 6 different microphysics schemes including the Kessler scheme (KS), Lin et al. scheme (LS), WSM-3 scheme (W3), WSM-5 scheme (W5), WSM-6 scheme (W6) and Eta scheme (Eta).

The Kessler scheme (Kessler, 1969) is a warm-rain scheme (it only considers the conversion between water vapour, cloud water and rain water), which is widely used for idealized modelling studies. Lin et al. scheme (Lin et al., 1983) is a more sophisticated scheme that includes warm rain fields and more variables like ice, snow and graupel processes. The difference between the WSM-3 and WSM-5 schemes (Hong et al., 2004) is that the later one allows for mixed-phase processes and super-cooled water. Ice and snow processes are both supported by these two schemes. In contrast, WSM-6 included graupel as a new term compared to WSM-5 (Hong and Lim, 2006). The Eta scheme (Rogers et al., 2001) is another relatively simple and efficient scheme with mixed-phase processes which is suitable for both fine and coarse resolutions.

In this chapter, for the purpose of verification, surface temperature and winds observations were obtained from all stations of four regions of at Wellington (3445), Auckland (1962), Christchurch (4843) and Whangarei (1283). Figure 6.1 shows the stations used for the verifications. Simulated rain rates were verified against the radar accumulation (calibrated by local rain gauges) observed by New Zealand National Radar Network.

The same cases as Chapter 5 were selected to evaluate the skills of the RK-nudging method. The nudging factor was chosen to be $3 \times 10^{-4} \text{ s}^{-1}$ for all cases in order to give the priority to the model physical and dynamical processes (Stauffer and Seaman, 1990). Horizontal and vertical influential radiiusees are given as 3.0 km and 0.1 η (4 vertical layers in this study). WRF configurations were set up the same way as Chapter 5. Considering that we only made a one-time nudging and the use of the liquid alone reflectivity assimilation operator (we did not consider the phase error over the time window), a short temporal influential radius was applied (30 min).

6.4 Results and Discussions
We compared the effects of different microphysics schemes on the simulations of temperature, winds and rainfall over all selected cases. Different statistical scores, including Probability of Detection (POD), False Alarm Ratio (FAR), Equitable Threat Score (ETS) and Frequency Bias Index (FBI), were used to verify the rainfall estimates.

Figure 6.2 - 6.5 show the statistics of (observation – forecast, OMF) at (T+1h, 30 minutes after the DA window) combined over all selected cases in terms of temperature and winds. For temperature, it appears that the Kessler scheme gave the lowest temperature estimates compared to all the others, and smallest bias could be found from it. In contrast, Eta showed the largest biases for almost all stations in the region of Christchurch, although for other regions, the difference caused by using different microphysics schemes were not significant. It is worthwhile to mention that, here we did not considered the observation errors, which might bring uncertainties to all of our verification results (in order to calibrate the observations, a long period statistics of (observation - background) is usually required, while the resources in the university is not allowed at present).

An average OMF at (T+1h) for temperature (Figure 6.3) supported above discussions, apparently, the Eta scheme has the most possibility of providing the highest temperature and the Kessler scheme provided the lowest temperature estimates for most cases. Overall, for temperature, the adjustments led by different microphysics schemes in the model (with the implementation of the RK-nudging) was moderate for most cases.

In contrast to temperature, the biases for winds led by the use of different microphysics schemes were trivial. It is almost impossible to tell the difference from the subjective evaluations for the OMF maps. However, the errors in the estimated winds were significant. For example, the maximum biases between simulations and observations could achieve 15.0\(\text{m s}^{-1}\) for U winds, and looks like even worse simulations were generated for V winds. It is apparent that the assimilation of rain rates using the RK-nudging scheme did not have the capability of improving wind estimates, which indicates that the assimilation of Doppler winds is still expected to work with the RK-nudging scheme for further improving precipitation forecasting. It is worth noting that, due to the main purpose of this study here is to investigate the difference caused by different model configurations with the implementation of the RK-nudging scheme, we applied U and V winds instead of wind direction and speed for the evaluations as they are the most direct outputs from the model.
The statistical scores for precipitation forecasts at T+1h (30 minutes after the DA window) in terms of different verification thresholds (0.05 mm h\(^{-1}\), 0.1 mm h\(^{-1}\), 0.5 mm h\(^{-1}\) and 2.0 mm h\(^{-1}\)) were presented in Figure 6.6. The truth field was the gauge corrected radar data resampled to 3.0 km. We find that the assimilation of rain rates with different microphysics schemes provided significant difference in the final rainfall estimates. For the threshold of 0.05 mm h\(^{-1}\), Lin et al. scheme (LS) obviously generated the highest skill in POD. In contrast, the Eta and Kessler schemes provided the lowest POD on average. For FAR at the threshold of 0.05 mm h\(^{-1}\), we find that the Eta scheme gave the lowest score while other schemes showed very similar skills on average. ETS considers both the correct and incorrect estimated grid points. We find that, for most cases, LS still gave the relatively higher ETS in general, and The Kessler scheme provided the lowest ETS on average. Compared to the scores obtained at the threshold of 0.05 mm h\(^{-1}\), POD and ETS decreased drastically with the threshold increased. Overall, LS and Eta provided the highest skill and the Kessler scheme presented the lowest skill on average. The difference in FAR due to different schemes were comparable to the POD and ETS scores, and generally, the Kessler scheme generated more false alarms compared to the others. Eta showed the lowest FAR but it is reasonable to assume that it was largely contributed by the underestimates from the scheme (e.g., we can tell it from POD). With the threshold increased to 2.0 mm/h, from POD, we find that intense precipitation still could not be predicted well. Similarly, ETS also decreased from 0.40 to 0.18, approximately and FAR increased correspondingly.

### 6.5 Conclusions

The RK-nudging scheme was developed according to the reverse Kessler scheme and the associated saturation adjustments. The skills of the nudging method with different microphysics schemes were investigated preliminarily in this chapter. We presented the sensitivity studies of the RK-nudging method with different cloud physics (microphysics) schemes: Kessler scheme (KS), Lin et al. scheme (LS), Eta scheme (Eta), WRF 3-class scheme (W3), WRF 5-class scheme (WP5) and WRF 6-calss scheme (WP6). Simulated temperature, winds and precipitation from WRF were evaluated using in situ observations in four different regions (Auckland, Whangarei, Christchurch and Wellington) or radar
data provided by NZ MetService Ltd. Different skill scores including Probability of Detection (POD), False Alarm Ratio (FAR) and Equitable Threat Score (ETS) were applied to provide the objective verifications for model simulated precipitation.

The results showed that although the connection between rain water and cloud water in the RK-nudging method is developed according to the simple liquid-only Kessler scheme, the use of the Kessler scheme for precipitation diagnostics in the model might not provide high skill on average. According to the selected cases studies, Lin et al. scheme (LS) provided the best precipitation simulation for most cases and the Kessler scheme provided the lowest skill, while the Eta scheme showed the lowest POD on average. All microphysics schemes, even with the initialization with radar data using the RK-nudging approach, could not predict intense precipitation very well.

For temperature simulation, we find that different microphysics schemes led to moderate changes. Overall, Eta provided the highest simulated temperature and the Kessler scheme estimated the temperature lower than all the others for most cases. However, it is apparent that all schemes are able to generate the temperature simulations in a good agreement with the associated observations.

For winds simulation, it is worthwhile to mention that, since the main purpose of the study in this chapter is to investigate the sensitivities of U and V winds in the model, we did not involve the bias discussions about wind speed and direction. It is clear that the difference led by the use of different microphysics schemes were trivial, which is understandable, as winds are not adjusted directly by any microphysics scheme. The assimilation of rain rates into NWP model using the RK-nudging scheme is not capable of adjusting the wind fields so well, which indicates that the assimilation of Doppler winds at the next step is quite necessary for improving precipitation forecasting further in New Zealand. The implementation of this process was reported in a thesis of Luke Sutherland-Stacey (2015).
Chapter 7. The effects of the assimilation of satellite retrieved clouds and precipitation on (very) short range precipitation forecasting in New Zealand

7.1 Abstract

New Zealand is an island country surrounded by the Tasman Sea and South Pacific Ocean. High impact weather systems, like heavy precipitation, frequently start and develop in the area out of the range of high resolution radar data. Thus, satellite data are expected to play an important role in the operational forecasting system of New Zealand. This chapter describes the assimilation of the satellite based precipitation analysis using the Reverse Kessler (RK) nudging scheme in New Zealand. Retrieved precipitating clouds were also incorporated into the model using the Water Vapour Correction (WVC) approach. The results from the assimilation of the “RainSat” analysis and precipitating clouds were compared to the radar alone assimilation experiments via both subjective evaluations and objective forecast skill scores. A total of 13 relatively heavy rainfall events occurred from November 2011 to January 2012 in New Zealand were selected to evaluate different data assimilation schemes. The results showed that, compared to the radar alone assimilation, using the “radar+satellite” merged analysis provided higher skill up to 9 hours on average within the radar range. In order to improve the ability of offshore forecasting, the assimilation experiments were also evaluated using the TRMM based rainfall analysis in the area out of the radar range. The results showed that, by using a simple nudging based approach, although we could find significant improvement in the skill scores at relatively low threshold, intense cells still could not be predicted well.

7.2. Introduction

Given a model is perfectly designed, Numerical Weather Prediction (NWP) is essentially an initial value problem and high resolution initial data for representing convergence, precipitation and clouds are necessary in order to improve the skill of NWP on a (very) short range (e.g., Austin et al., 2012; Sokol, 2009). An effective approach is to initialize the model with a relatively accurate background by the incorporation of radar observed reflectivity and Doppler velocity (Sun et al., 2013; Sun and Wang, 2013; Sun, 2005; Sun and Crook, 1997; Barker et al., 2004; Barker et al., 2012; Huang et al., 2009; Wang et al.,
Chapter 7. The effects of the assimilation of satellite retrieved clouds and precipitation on (very) short range precipitation forecasting in New Zealand

2013a; Wang et al. 2013b; Zhang et al., 2004; Caya et al., 2005; Xiao et al., 2005). In New Zealand, radar data assimilation experiments have been carried out and presented recently by Austin et al., (2012) and Zhang et al. (2012). The results showed that the improvements led by the assimilation of radar reflectivity using the RK-nudging approach (Zhang et al., 2014) could last up to 7-9 hours on average, which would be beneficial for local nowcasting and very short range precipitation forecasting.

For an island country like New Zealand, many weather systems develop very fast from the Tasman Sea without being previously detected by radars. In addition, when the model background is very stable and does not support the development of convection, the radar observed precipitation is usually too weak to trigger precipitating processes in the model (Sokol, 2009), which means that precipitation forecasting may not be improved even if reflectivity is incorporated. Moreover, previous studies have indicated that cloud-affected areas usually agree with the areas that have large forecast errors (McNally, 2002; Bauer et al., 2011). This means that the useful clouds/precipitation data observed by satellite can be essential to improve the clouds and precipitation adjustments in a model for (very) short range precipitation forecasting.

Satellite based observations have been widely used to improve the initial conditions of the NWP models for many years. Satellite observed radiance is widely used in data assimilation. However the conversion from radiances to profiles of temperature and humidity is an ill-posed problem unless additional ‘background’ information is used (Rodgers 1976; Eyre and Lorenc 1989; Anderson et al., 1994). Retrieval schemes include the use of statistical information (e.g. Reale et al.1986), or using the radiances themselves to pick a background profile from a library of representative atmospheric profiles (e.g., Fleming et al., 1986). Anderson et al (1994) also demonstrated the benefits by the use of the NWP forecast model to provide the background information with variational approach. Significant improvements were found from the assimilation of radiance (e.g., Ebert et al.; 2007), while it is worthwhile to mention that the relatively high skill of NWP precipitation forecast is most related to mean statistics over a certain period (e.g., 6-12 hours) (Lopez ,2011; Bauer et al., 2011), significant errors still exist when making the instantaneous verifications at grid-by-grid basis. In order to improve the Quantitative Precipitation Forecast (QPF) on a (very) short range, precipitation related fields are expected to be assimilated into model, although the errors inherent in the retrieved
precipitation may be significant, and the effects of assimilation usually disappear rapidly after several hours due to the introduced imbalance of the model state, and also the climatology of the model being inconsistent with the assimilated observations.

Efforts have been made to assimilate satellite retrieved precipitation into a model over last several decades. At the UKMO, Moisture Observation Preprocessing System (MOPS) was developed (Macpherson et al., 1996). In this system, latent heat nudging method (Jones and Macpherson, 1997) was used to assimilate relative humidity profiles retrieved from the 3D cloud analysis. Similar approaches were also described by Montmerle et al. (2007) and Kopken et al. (2004). Precipitation retrieved from satellite data can be assimilated directly using the methods similar to that applied to radar data (e.g., Manobianco et al., 1994; Davolio and Buzzi, 2004; Sokol, 2009) and it is considered as the most straightforward way to use clouds/precipitation affected observations from satellite to initialize NWP models.

In this chapter, a method called Reverse Kessler Nudging (RK-nudging) (Zhang et al., 2014) was applied to assimilate precipitation retrieved from both radar and the “RainSat” technique (this approach is also described in Chapter 5). Radar retrieved rain rates were assimilated within the radar detection range and the “RainSat” analysis was applied to the area without radar coverage. Water Vapour Correction (WVC) scheme (Sokol and Rezacova, 2009; Sokol, 2009) was also employed to incorporate satellite estimated precipitating clouds, radar reflectivity and the “RainSat” analysis for the contrast experiments. Weather Research and Forecasting (WRF) model is used to provide precipitation forecasts at the spatial resolution of 3 km for the same 13 cases used in Chapter 5 and 6. The forecasts were verified against hourly radar rainfall accumulation and TRMM Multi-satellite Precipitation Analysis (TMPA).

### 7.3 Methodology

#### 7.3.1 Precipitation analysis retrieved from satellite

In this paper, the “RainSat” technique (Lovejoy and Austin, 1979; Bellon et al., 1980) has been applied to delineate precipitation over the area of interest using the Geostationary Operational Environmental Satellite (GOES) data. The “RainSat” technique, which considers both the visible (VIS) and infrared (IR) observed radiances and radar data, is
established according to the assumption that cold and bright clouds may yield higher probability of precipitation. Previous studies showed that this method is able to show reliable retrieved results compared to IR-alone method for the warm and orographically induced rainfall in most cases (e.g., King et al., 1989; King et al., 1995). The implementation of the “RainSat” technique in New Zealand can be found in Chapter 2 and 3.

Another method for delineating precipitation from satellite used in this chapter is based on the recognition of precipitating clouds (Kidder et al., 2005). This method was originally tested for Meteosat-8 data: the brightness temperature difference between 6.2 um and 10.8 um channels are applied to determine the high and thick clouds, which are likely to be precipitating. Empirical values were applied to flag the precipitating clouds by Kidder et al. (2005) or other similar studies (e.g., Sokol, 2009, 2014). In this study, the GOES imager (GOES-west) with the central wave length of 6.7 um (channel 3) and 10.7 um (channel 4) were used. Channel 3 is more sensitive to cloud cover and height and Channel 4 is relatively more sensitive to water vapour. In order to decrease the false warnings, we used the algorithm/parameters adopted by Sokol (2009). The main advantage of this method compared to the “RainSat” technique is that it is able to delineate precipitation 24 h every day while for the “RainSat” technique, the VIS data are not available during the night-time.

Figure 7.1 gives two examples of radar observations and the associated satellite derived precipitation. The units for radar observation, “RainSat” retrieved precipitation and IR retrieved precipitation area are dBZ, probability (percentage) and temperature difference (K), respectively. We can see that, compared to the infrared alone approach, the “RainSat” technique has the capability of generating more accurate precipitation estimates (for precipitation area) compared to the radar data. However, because there are no direct rainfall observations over the Tasman Sea, it is difficult to determine the skills of different satellite based rainfall estimates out of the radar range.

In this chapter, a method described by Zhang and Austin (2013) was applied to determine the precipitation intensity for the “RainSat” technique (see Chapter 3). This process was done automatically by computer: the rainfall area was reduced by increasing the probability threshold from the minimum of 10% to the maximum of 100%, and matching the rainfall area to different radar thresholds.
7.3.2. Data assimilation schemes

In this chapter, radar reflectivity was assimilated using both the RK-nudging method and the WVC method (Sokol and Rezancova, 2006). The detailed description of the RK-nudging scheme can be found in Chapter 5 and Zhang et al., (2014).

There is another empirical nudging scheme, WVC approach, developed by Sokol and Rezacova (2006) for incorporating satellite precipitating clouds in the model. The scheme uses satellite retrieved temperature from two channels of GOES Imager data: 10.7 um and 6.7 um. In this chapter, the satellite data were interpolated into the spatial resolution of 5.0 km x 5.0 km before the assimilation processes. WVC adjusts water vapour at the grid point with:

\[ T_{10.7} - T_{6.7} \leq 8K \]  

(7.1)

The relationship developed by Hagen and Yuter (2003) is used to convert observed rain rates R to the water vapour mixing ratio \( q_v \) (kg kg\(^{-1}\)):

\[ q_v(R) = \frac{70.2026 \times 10^{-6}}{\rho} \times R^{0.9143} \]  

(7.2)

Where \( \rho \) represents the air density (kg m\(^{-3}\)). It is worth noting that both Equation (7.1) and (7.2) are far from accurate (e.g., Hagen and Yuter, 2003; Sokol, 2009). We assumed that the difference between the model rain water (calculated by Equation (7.2)) and the observed rain water can be denoted to D, we have:

\[ D = q_v(R_{obs}) - q_v(R_{mod}) \]  

for radar

\[ D = \max[w(z_k)c - (q_r + q_g + q_i + q_s), 0] \]  

for satellite

(7.3)

Where \( R_{obs} \) and \( R_{mod} \) indicate the observed and simulated rain rates, respectively. \( w(z_k) \) is a factor as a function of the data height \( z_k \). According to Sokol (2009), \( w(z_k) \) is defined as:

\[
\begin{align*}
  w(z_k) &= 0 & 
  z_k &\leq 1000m \\
  w(z_k) &= \frac{z_k - 1000}{500} & 
  1000 < z_k &\leq 1500m \\
  w(z_k) &= 1 & 
  1500 < z_k &\leq 5000m \\
  w(z_k) &= 1 - \frac{z_k - 5000}{5000} & 
  5000 < z_k &\leq 10,000m \\
  w(z_k) &= 0 & 
  z_k &> 10,000m
\end{align*}
\]

(7.4)
The vertical distribution of $w(z_k)$ is shown in Figure 7.2. It is apparent that, if $D > 0$, precipitation is underestimated by the model and $q_v$ should be increased according to the following equations:

$$q_v^{\text{new}} = q_v + DIF$$

(7.5)

Where $DIF = \min [w(z_k) \times \alpha \times D, \delta]$ and $\delta = \max [\varepsilon_v \times q_v^s - q_v, 0]$. Here, $\alpha$ and $\varepsilon_v$ are constants that usually have to be determined according to a number of cases studies. $q_v^s$ is the value of saturated water vapour. $q_r$, $q_s$, $q_g$, $q_i$ and $q_c$ are model mixing ratio of rain, snow, graupel, ice and cloud water, respectively. $c$ is defined as:

$$c = 0.0001 \times \min \{0.5 \times [9 - (T_{10.7} - T_{6.7})], 2\}$$

(7.6)

If $D < 0$, then $q_v$ can be calculated based on $q_v^{\text{new}} = q_v - DIF$ with $\delta = \max (q_v - \varepsilon_v \times q_v^8, 0)$. It is worth noting that all the constants used in this paper for the WVC approach were simply adopted from the preliminary tests by Sokol (2009, 2010), and there is no sensitivity studies of the WVC approach carried out in New Zealand before. By configuring the WVC approach with better estimates of empirical coefficients may provide further adjusted results in New Zealand.

### 7.3.3. Model configuration

In this chapter, the same domain configuration was applied as Chapter 5 and 6. High resolution observations (from radar and satellite) were incorporated into the model with previous 6 hours free forecasts (compared to the experiments carried out in Chapter 5, we would not expect to apply the assimilation of satellite retrieved rain rates in a 3 hours cycle system considering the time required for data retrieval and postprocessing). Verifications were carried out with radar data or TMPA after the assimilation time window. It is worth noting that, similar to Chapter 5 and 6, only one time nudging was carried out for each selected case, thus there was no phase change error considered in this study. The Kessler scheme (Kessler, 1969) was adopted for microphysics processes in the model. Other parameterizations used include the Rapid Radiative Transfer Model (RRTM) scheme (Mlawer et al., 1997) for long wave radiation and the Dudhia scheme (Dudhia, 1989) for short wave radiation and the Yonsei University (YSU) scheme (Noh et al., 2003) for planetary boundary layer parameterization.

### 7.4 Cases studies
The same cases as last chapters are used here. Infrared and visible images from GOES data presented the cloud evolution during the entire period of interest. Radar data caught the high impact weather systems at the distance of maximum of about 200 km from the coast. In this section, we give the detailed analyses for two cases (01 November 2011 and 31 December 2011) among the 13 selected events for showing the adjustments due to the assimilation.

7.4.1. Event: 01 November 2011

A low pressure system initiated over the Tasman Sea and moved eastward. Intense precipitation was recorded by radars from 2000 UTC 31 October 2011. The WRF model was initialized at 1800 UTC 31 October. Radar data and the “RainSat” estimated rain rates were assimilated 6 hours later at 0000 UTC 01 November 2011. Precipitating clouds were also incorporated into the model at 0000 UTC 01 November using the WVC approach.

Figure 7.4 shows simulated vertical cross sections of cloud water (shaded) and rain water (contoured) for Case 1 (at 35.5°S) in terms of the RK-nudging and the WVC approach (the associated vertical slice for Control is shown in Figure 7.3 (top)). In this figure, RK-radar and WVC-radar indicate the methods of radar assimilation adopted. RK-RadSat and WVC-RadSat indicate the “radar+RainSat” assimilation experiments with the RK-nudging and the WVC approaches, respectively. For RK-RadCld, radar reflectivity was assimilated using the RK-nudging scheme while precipitating clouds were assimilated with WVC. For WVC-RadCld, both radar reflectivity and precipitating clouds were incorporated using the WVC approach (see Table 7.1).

It is apparent that the RK-nudging approach has the capability of providing more adjustments in cloud water and rain water corresponding to the observations. RK-RadSat scheme generated more rain water compared to the others (e.g., the areas from 170.0° to 172.35° and from 172.7° to 173.05°). In contrast, WVC-radar and WVC-RadSat provided very similar results and no significant rain water was obtained on the ground. Since it is not easy to tell the difference between the vertical slice of WVC alone method and the Control experiment, the vertical slice of (Control – WVC-radar) is shown in Figure 7.5 (top), we find that slight adjustment was made from 172.0° to 172.7°. Seems WVC-RadCld provided more significant adjustment, from Figure 7.4, the most significant changes made
by WVC-RadCld were made from 172.1° to 172.3°.

Figure 7.6 provides the comparisons of CTL, RK-radar, RK-RadSat, RK-RadCld and the associated observations at the lead time of 1 h, 3 h and 6 h. It is apparent that CTL and WVC-RadSat provided the lowest skill on precipitation forecasts over the entire period. For 01 UTC, both experiments missed the precipitation located along the west coast of the North Island. Other schemes provided very similar results. The main rain band was presented by RK-radar and RK-RadCld but it located about 150 km away from the west coast. The main rain band simulated by RK-RadSat was relatively more realistic but it was still not capable of showing the precipitation near the regions of Auckland and Waikato. For all schemes, compared to the observations, additional rainfall was simulated in the bottom of the South Island, however, it is difficult to tell whether the simulations were correct or not as radar could not get any useful information in this area because of the terrain blocking. After 2 hours (0300 UTC), Most RK related experiments gave very similar simulations, which were slightly better than CTL and WVC-RadCld. However, the precipitation intensities for the schemes using the RK-nudging approach were largely overestimated and the movement and development of precipitation could not be represented well. In contrast, WVC-radar+RainSat provided trivial impacts on the forecasts. At 0600 UTC, from subjective evaluation, the RK-RadSat/RK-RadCld schemes provided the highest correlation to the associated observations in general (Among them, seems RK-RadSat showed better forecasts due to the rain simulated in the Waikato region). The main rain bands simulated by both CTL and WVC alone approach were still located very far away from the west coast. All simulations overestimated rain rates, especially in the area near the edge of the radar range.

From the subjective evaluations, we find that for Case 1, the assimilation using the RK-nudging method resulted in more obvious (positive) effects compared to the assimilation using the WVC method alone. By the incorporation of satellite retrieved rain rates and precipitating clouds, moderate improvements were presented after about 4-5 hours, which indicated that the adjustment of the moisture fields over the Tasman Sea might lead to higher skill of precipitation forecasts in New Zealand.

7.4.2. Event: 31 December 2011

Similar to the Event 1, a low pressure system initiated and developed over the Tasman Sea
Chapter 7. The effects of the assimilation of satellite retrieved clouds and precipitation on (very) short range precipitation forecasting in New Zealand

and gradually moved eastward from 28 December 2011. The North Island was affected by heavy rainfall from about 1500 UTC 29 December. The precipitation resulted in severe flooding and landslides in the regions of the Northland, Wellington and Palmerston North. For Case 2, radar reflectivity and the satellite retrieved precipitation/clouds were assimilated at 0000 UTC 31 December. Verifications of the simulations against the associated radar data were carried out from 0100 UTC to 1200 UTC 31 December.

Figure 7.7 shows the vertical slices for different data assimilation experiments obtained at the latitude of 35°S (The associated vertical slice for CTL can be found in Figure 7.3). It is apparent that the assimilation of the “RainSat” analysis has the capability of adjusting both cloud water and rain water significantly. For example, in the area between 176.3° and 176.7°, high clouds were generated by the assimilation of the “RainSat” analysis using the RK-nudging method and this resulted considerable precipitation in the region. However, it is apparent that over the area from 176.88° to 177.3°, cloud water has been reduced by the incorporation of the "RainSat" analysis. Similar to Case 1, the adjustment led by the assimilation using WVC method was still trivial (see Figure 7.5 (bottom)). It is worthwhile to mention that rain water was reduced by using the WVC method for the “RainSat” analysis between 176.2° and 176.53°, which provided the opposite adjustment as the one made by the RK-nudging method. The possible reasons include the overestimated rain water by the RK-nudging approach, and also the errors inherent in the current configurations of the WVC approach. Detailed discussions are presented in Section 7.7.

Figure 7.8 gives 6 h precipitation forecasts with different data assimilation schemes and the associated radar accumulations. From the forecast at 0100 UTC, we find that slight improvements were made by the assimilation of the “RainSat” analysis over the Waikato Region. Similar to the Case 1, no schemes were able to reduce the spurious rainfall simulated in the region from Taupo to Palmerston North. At 0300 UTC, rainfall intensities were overestimated in the Waikato-Taupo region by all simulations. “RK-RadSat” provided the highest correlation to the associated observations overall. In contrast, spurious precipitation still existed along the east coast of the North Island, and there was no rainfall estimated in the region of Tauranga and Rotorua relative to the observations. At the lead time of 6 hours 0600 UTC, all data assimilation schemes using the RK-nudging approach generated very similar results and considering the wider spread rain estimated in the central
North Island, they have slightly higher skill than the Control experiments. Similar to Case 1, WVC-RadSat provided the trivial adjustments compared to CTL. In conclusion, very similar results were obtained from the evaluation of Case 2 compared to Case 1. The assimilation using the RK-nudging scheme produced the highest skills for the first 3-4 hours. The difference is that for Case 2, the assimilation of precipitating clouds did not introduce improvement after several hours compared to the reflectivity alone assimilation.

### 7.5 Objective evaluations

A total of 13 relatively heavy rainfall cases occurred from November 2011 to December 2012 were evaluated using different objective skill scores including POD, ETS, FAR and the spatial scale based score FSS. All scores were calculated within the radar range. Radar data obtained from New Zealand National Radar Network were used to provide “ground truth” for the verifications. All radar data used in this chapter were calibrated with the corresponding rain gauges data, which were obtained from CliFlo system of NIWA.

Figure 7.9 shows the combined POD, ETS and FAR scores that were calculated at the spatial scale of 3 km over the whole New Zealand. From POD statistics, we find that the assimilation of "Radar+RainSat" and "Radar+Clouds" have the capability of providing higher scores on average compared to other schemes. For example, for the POD skill scores at threshold of 0.2 \( mm \ h^{-1} \), RK-RadSat provided the highest skill for the first about 4 hours, and then it was outperformed by RK-RadCld. RK-Radar provided a higher score compared to CTL or other WVC related experiments for the first 2-3 hours. All WVC-related simulations gave very similar results to the CTL experiments. Slightly poorer results were obtained by the precipitating clouds assimilation for the first 3 hours. Similar results were found from the ETS statistics at the threshold of 0.2 \( mm \ h^{-1} \). However, it is apparent that RK-RadCld provided the lowest FAR during the entire verification period. In addition, the FAR of RK-RadSat was lower than RK-Radar, CTL or any WVC-related simulations for the first about 4-5 hours while after that all simulations gave very similar scores except for the experiments of RK-RadCld.

As the verification threshold increased, the skill of simulations dropped rapidly. For example, the maximum of ETS obtained at the threshold of 0.2 \( mm \ h^{-1} \) for CTL was about 0.13 while it decreased to about 0.014 when the threshold increased to 5.0 \( mm \ h^{-1} \). The
distributions of the skills in terms of different data assimilation schemes were very similar for the threshold between 0.2 $\text{mm h}^{-1}$ and 2.0 $\text{mm h}^{-1}$: the assimilation of “reflectivity + RainSat” analysis using the RK-nudging scheme (RK-RadSat) provided the highest skill for the first several hours while after that, the assimilation with both the observed "reflectivity" (using RK-nudging) and precipitating clouds (RK-RadCld) performed relatively better results. In general, the assimilation of both radar and satellite retrieved clouds/precipitation data has the capability of improving precipitation forecasting compared to the control experiments, and the new developed RK-nudging method might provide more significant adjustment compared to the WVC approach on average. With the threshold increased to 5.0 $\text{mm h}^{-1}$, all scores were very small and it is apparent that although high resolution remote sensing data were incorporated in the model, the model was still not capable of estimating small and intense cells adequately.

Figure 7.10 shows the FSS combined over the 13 selected cases in terms of different thresholds (0.2 $\text{mm h}^{-1}$, 0.5 $\text{mm h}^{-1}$, 1.0 $\text{mm h}^{-1}$, 2.0 $\text{mm h}^{-1}$ and 5.0 $\text{mm h}^{-1}$) and different spatial resolutions (from 3 km to 150 km). For a relatively small threshold (e.g., less than 1.0 $\text{mm h}^{-1}$), the assimilation of radar reflectivity and the “RainSat” analysis provided the highest skill at high resolution verifications (e.g., at the spatial scale of 3 km) for the first several hours. However, when the verification scale decreased to about 10.0 km, additional precipitating clouds assimilation gradually outperformed the “radar+RainSat” scheme. In addition, only trivial adjustments were found from the WVC alone related schemes, especially for the lead time for the first 1-2 hours. For the lead time of 9 hours, “RK-RadCld” assimilation provided relatively higher skill on average. With the threshold increased, it is apparent that the improvements led by the assimilation of precipitating clouds using WVC method decreased gradually, especially for the first 3 hours. For example, for the lead time of 1 h, at the verification scale of 100 km for the threshold of 1.0 $\text{mm h}^{-1}$, FSS was 0.37 and 0.3 approximately for “RK-RadCld” and “RK-RadSat” schemes, respectively. While at the scale of 100 km for the threshold of 5.0 $\text{mm h}^{-1}$, FSS for “RK-RadSat” was decreased to about 0.15, which was slightly higher than the score for “RK-RadCld” (0.13). However, for the forecasts after about 3-5 hours, the “RK-RadCld” scheme still has the capability of providing higher skill scores over large spatial scales for most selected cases in this study.
Chapter 7. The effects of the assimilation of satellite retrieved clouds and precipitation on (very) short range precipitation forecasting in New Zealand

7.6 Verifications against TRMM Multi-Satellite Precipitation Analysis

The verifications in Section 7.5 were all carried out within the range of the New Zealand National Radar Network. However, the forecasting over the Tasman Sea also plays an important role for the risk management of offshore businesses like fishery and marine transportation in New Zealand. In this section, therefore, we investigated the effects of different assimilation schemes on the skill of precipitation forecasting over the Tasman Sea (out of the range of National Radar Network).

TRMM Multi-Satellite Precipitation Analysis (TMPA) over the Tasman Sea was used to be the “truth field”. TMPA was obtained at the spatial resolution of 0.25° × 0.25° before the resampling for the purpose of verification. The algorithm uses precipitation estimates from different instruments like the TMI, AMSR0E, SSMI, SSMI/S, AMSU, MHS and IR to generate the best guess rain rates globally. In the algorithm, Microwave data are calibrated to TRMM Combined Instrument (TCI) precipitation estimates. Huffman (2013) gives a detailed description of the TMPA algorithm. Considering the resolution of the model configuration and TMPA analysis was different in this chapter, TMPA analysis was interpolated into the same grid point as the NWP model, which means that the verifications were carried out at the spatial resolution of 3 km but the actual resolution of the “truth field” in this paper was only 25 km on average.

In this section, we presented different objective statistical scores for showing the skills of different data assimilation schemes over the Tasman Sea. Figure 7.11 shows the average POD scores. We find that for the first 3 hours, “RK-RadSat” provided the highest skill for all verification thresholds, while after about 6 hours, precipitating clouds assimilation (e.g., RK-RadCld) performed slightly better compared to other schemes, which was similar to the verifications carried out within the radar range. In addition, it is apparent that the assimilation of radar reflectivity alone was not capable of improving precipitation forecasting in the area out of the radar range. For a relatively large verification threshold (e.g., 0.5 mm h⁻¹), the perturbation caused by the assimilation of radar reflectivity had the potential risk to disturb the model’s physical stability, and this instability might spread to the area out of the radar range and led to negative effects on the precipitation forecasting in such area. Moreover, in accord with above verifications, RK-nudging method had the capability of providing more adjustments in comparison with the WVC approach.
Figure 7.12 and Figure 7.13 give the average ETS scores and FAR scores in terms of different thresholds obtained over the Tasman Sea. Very similar results to the POD could be found from the ETS statistics. For a 3 h forecast, it is apparent that RK-RadSat provided the highest skill, while WVC-RadSat provided very similar scores to the Control experiments. The assimilation of precipitating clouds led to poorer simulations compared to Control in general, which indicated that the roughly estimated precipitation clouds might bring negative effects to the very short range NWP forecast (3 h). In contrast to 3 h forecast, the assimilation of precipitating clouds produced very similar or even slightly better results compared to Control at the lead time of 6 hours, which indicated that this adjustment might have more positive effects for relatively longer range forecasts. For the 9 h forecast, it is apparent that the experiment of “RK-RadCld” provided the highest score and others have very similar skills on average, which agrees with the analysis of the PODs (Figure 7.11).

We find very similar statistics from FAR scores (Figure 7.13), although the difference in FAR for different data assimilation schemes were not as significant as other scores. For example, for the 3 h forecast at the threshold of 0.2 \( mm \ h^{-1} \), the lowest FAR was about 0.43 (“RK-RadSat”) and the highest FAR was only about 0.49 (“RK-RadCld”). The difference between the highest FAR score and the lowest FAR score became larger with the verification threshold increased. When the threshold was over 2.0 \( mm \ h^{-1} \), FAR scores were already very high for all NWP schemes.

FSS were also investigated in the area out of the radar range (figures not shown). Similar results as ETS were obtained: (1) “RK-RadSat” introduced slight improvements for the first 3-4 h forecasts while after that “RK-RadCld” might be able to show higher skill, especially over relatively large scale. (2) The assimilation of radar reflectivity usually has trivial effects on the precipitation estimates over the Tasman Sea. Moreover, both objective and subjective evaluations presented in this chapter showed that no schemes were capable of delineating small and intense cells adequately.

7.7 Discussions
From the above studies, it is apparent that, although the WVC approach was able to improve the precipitation forecasting over the lead time of several hours ahead, the effects
were not as significant as the RK-nudging approach. There are several reasons that have been partially summarized by Sokol and Rezacova (2009). One significant reason is that the parameters of WVC approach are largely dependent on the model parameterization of precipitation, and the configuration of the vertical nudging profile. For example, from Sokol and Rezacova (2006), three cases were used and constant values of $\alpha$, $\varepsilon_+$ and $\varepsilon_-$ were selected as 0.001, 1.02 and 0.95, respectively, with no vertical nudging profile applied. While in Sokol and Rezacova (2009), $\alpha$ was set to be 0.05 for another five precipitation events, which was much higher than that from the case studies in 2006. Another study (Sokol, 2009) using the WVC approach, which involved radar and satellite assimilation, set $\alpha = 0.1$ and with a slight different vertical nudging profile configurations compared to the one used in Sokol and Rezacova (2009). It is apparent that, the constant values in the WVC approach may be sensitive to different cases. Several sensitivity studies were carried out (Sokol and Rezacova, 2006) with the values of $\alpha$, $\varepsilon_+$ and $\varepsilon_-$ ranged from [0.00001, 0.01], [1.005, 1.2] and [0.8, 0.99], respectively. Two criteria might be applied during the process of the selection of those constants: one is that the precipitation evolution during the assimilation should be in accord with the radar observations. The other one is that the abrupt and large changes in one time step should be avoided in order to maintain the stability of the model.

From the above discussions, we may be able to expect better results from the WVC approach in New Zealand by selecting the parameters more carefully (e.g., with a long period of sensitivity studies using different sets of WVC related parameters), or by improving the configurations of the vertical nudging profile with more detailed preliminary tests (e.g., Sokol and Rezacova, 2009). For example, reducing the minimum assimilation height from the current 1,500 m to hundreds meters for involving lower level radar observations (Sokol, 2009). However, Sokol (2011) also indicated that it is easy to generate unrealistic humidity vertical profiles for some cases at relatively lower levels.

However, the sensitivity study of the WVC approach is not the main objective of this paper since what we look forward to investigating is that whether the assimilation of satellite data over the Tasman Sea could improve the (very) short term precipitation forecasting in New Zealand. From above statistics, it is apparent that both the WVC approach and the RK-nudging approach have the capability of using satellite retrieved precipitation information.
and, more or less, improving the precipitation forecasts up to about 9 hours ahead.

It is also worthwhile to mention that there are significant errors inherent in the RK-nudging method as well, which have been discussed and summarized in Chapter 5 and Chapter 6. First, the RK-nudging scheme is established based on the simple, liquid-only Kessler warm rain processes. Even for a strict warm rain process, the empirical relationship used in the Kessler scheme may still have significant errors (e.g., Seifert and Beheng, 2001; Rognvaldsson, 2013). In addition, in the RK-nudging scheme, oversaturation is not allowed and this may lead to the overestimation of rain rates. The risks of using the nudging approach, such as the arbitrary strength and arbitrary spatial and temporal extent of the weighting function, also contribute to the uncertainties in the forecasts.

Besides the uncertainties existing in the data assimilation scheme, there are also many factors affecting the skill of the retrieved "RainSat" analysis, which were used to initialize the model in this chapter. Chapter 3 gives the detailed illustration about the errors inherent in the “RainSat” technique. In comparison with the “RainSat” analysis, precipitating clouds used in this chapter usually have much larger area. Unlike the rainfall delineated by the “RainSat” technique, it provided the clouds estimates with identical skill over the whole area of interest, which means that the “RainSat” technique may provide more estimates that are accurate in the area not far away from the radar range while beyond that, the estimates of precipitating clouds may have higher skill.

7.8 Conclusions
In this chapter, we investigated the effects of the assimilation of radar/satellite retrieved clouds/precipitation for the (very) short range precipitation forecasting in New Zealand. The “RainSat” technique was used to delineate precipitation over the Tasman Sea. Precipitating clouds were estimated using the method described by Kidder et al. (2005). Different data assimilation schemes were used in this chapter: in the area within the radar range, radar reflectivity was incorporated into the model using the RK-nudging method and the WVC method. For the area out of the radar range, the “RainSat” analysis was assimilated into the model using both the RK-nudging and WVC methods, while precipitating clouds were assimilated using the WVC method only. Different combinations of data assimilation methods were applied in this paper. In contrast, the Control
Both subjective and objective approaches were used to investigate the effects of the assimilation of radar reflectivity and satellite retrieved clouds/precipitation data. From vertical slices of the cloud/rain water for the two cases occurred on 01 UTC 01 November 2011 and 31 December 2011, we find that the RK-nudging method was capable of adjusting the moisture fields according to the associated observations well. While only trivial effects were detected using the WVC method alone. The subjective evaluations for these two cases showed that the assimilation of satellite retrieved clouds/precipitation generated higher skill on average compared to the radar reflectivity assimilation and the Control experiments up to 9 hours. However, spurious rainfall still could not be addressed so well by all data assimilation schemes used in this chapter.

A total of 13 heavy rainfall cases were selected to investigate the skill of different data assimilation schemes. Combined objective scores including POD, ETS and FAR showed that the assimilation of "reflectivity+RainSat" analysis using the RK-nudging method has the capability of providing the highest skill for the first 0-4 hours approximately, and after that, the scheme of "RK-radar+Cloud" (RK-nudging and WVC were used for assimilating radar reflectivity and precipitating clouds, respectively) might give slightly higher scores. In contrast, the assimilation using the WVC approach alone gave trivial effects overall. For the verifications carried out in the area out of the radar range, we find that the assimilation of radar reflectivity was not able to improve offshore precipitation forecasting at all. Similar to the scores obtained within the radar range, the scheme of using the RK-nudging method with both radar and the “RainSat” analysis provided the highest skill for the first several hours in general.

The errors inherent in the assimilation experiments in this chapter were also discussed. These include the errors in the selection of empirical coefficients for WVC, the errors existing in the use of the relatively simple RK-nudging method and the errors inherent in the "RainSat" technique and the estimates of precipitating clouds.

Overall, we find that the assimilation satellite retrieved clouds/precipitation over the Tasman Sea has the potential to improve precipitation forecasting in New Zealand. The “RainSat” analysis may be beneficial for a very short range forecasting, and beyond that,
the assimilation of precipitating clouds using the WVC approach might be helpful. The improvements provided by the assimilation of satellite retrieved information last up to about 9 hours. We hope longer effective periods can possibly be achieved by using other more complicated data assimilation methods like 4DVar or EnKF, which demand expensive computational resources but have the virtue that they consider both the errors of observation and model background during the assimilation processes.
Chapter 8. Using nowcasting data to initialize high resolution NWP model for improving precipitation forecasting in New Zealand

8.1 Abstract

It is clear that extrapolation based nowcasting usually has higher skill for the 0-1 h precipitation forecasts than NWP models (e.g., Wilson, 1998). It is reasonable to assume that, therefore, by using the 1 hour nowcast to adjust the associated model background, the beneficial effects of the initial conditions can be significantly prolonged and therefore we can reasonably expect further improvements in precipitation forecasting compared to the traditional methods which only include observed data. In this chapter, we investigated the effects of applying both the radar and “RainSat” based nowcasting data, which were generated using the cross-correlation method, to adjust the model water vapour profile at the lead time of 1 hour. A reverse Kessler precipitation nudging scheme is adopted in this chapter to incorporate data into the model. Verifications were carried out within the range of New Zealand National Radar Network. The Same cases used in Chapter 5 were employed in this chapter. Both the subjective and objective evaluations showed that the assimilation with observation and nowcasting data together provided the highest skill on average up to about 6-9 hours compared to the “one time” reflectivity nudging experiments, and all data assimilation schemes had the capability of producing higher skill compared to the control experiments. The results indicates that the assimilation of nowcasting data has the potential to further improve the current rapid update system.

8.2 Introduction

One of the most critical problems of numerical weather prediction (NWP), especially on the very short time scale, is the initial values issue (e.g., Sun and Crook, 1997;
Chapter 8. Using nowcasting data to initialize high resolution NWP model for improving precipitation forecasting in New Zealand

Zhang et al., 2004; Barker et al., 2004, 2012). However, due to the “spin-up” problem and the unavoidable errors (e.g., initial conditions are usually obtained from the data which have the resolution less than the one that model has (Sokol and Zacharov, 2012)) existing in the NWP models, it is very difficult to initialize the model with very accurate fields. One useful approach for improving the quality of model background is to assimilate high resolution observations.

Nudging based assimilation approaches, such as RK-nudging and WVC method, have been tested in New Zealand (Zhang et al., 2012; Zhang and Austin, 2013; Zhang et al., 2014). The RK-nudging method avoids the linearization error (e.g., in WRF 3D-Var forward operator) and expensive computational resources. Cases studies in Chapter 5 showed that, by initializing the model with high resolution radar reflectivity data using the RK-nudging method, the precipitation forecast could be improved up to about 7-9 hours on average over the whole New Zealand.

For convective scale data assimilation, the type of data to be incorporated would largely determine the effects of assimilation. Model initialization with the high resolution observed clouds/precipitation data has been widely investigated over last several decades (e.g., Sun et al., 2014). While even with high resolution observations assimilated, NWP is still considered as a method that provides less skill in comparison with the simple extrapolation based nowcast for the first 1 hour or even slightly longer (e.g., Sokol and Rezankov, 2012; Ruzanski, 2010). This suggests that, by using the nowcasting data to adjust the model estimates at the lead time of 1 hour, we can add more constraints and thus the model may behave better. (e.g., Sokol and Rezankov, 2012). For example, in Figure 8.1, the skill of nowcasting (indicated by the dash-dot line) is higher than any NWP configurations (the skill of NWP model initialized without (with) high resolution observations is represented by the solid (dashed) line) at the lead time of 1 h, which means that it may be beneficial for using the 1 h nowcasting data to adjust the model background correspondingly. Considering the effects of the prolonged initial conditions at (T+1), higher skill of precipitation
forecasting is expected to be obtained for subsequent hours (represented by the dot line).

In this chapter, we describe the effects of assimilating 1 h extrapolated precipitation in WRF for New Zealand. Section 8.3 describes the data assimilation schemes and the nowcasting approach used in this chapter. Followed by the discussions of the results in Section 8.4 and a conclusion is given in Section 8.5.

8.3 Methodology

8.3.1 Data assimilation scheme
In this chapter, radar and satellite retrieved rain rates were assimilated using the RK-nudging approach (Zhang et al., 2014). The Kessler warm rain processes are reversed in the RK-Nudging for improving precipitation forecasting according to the adjusted water vapour $q_v$. The assimilation scheme starts by converting observed reflectivity (or rain rates) to rain water $q_r$ using the empirical relationship described by Sun and Crook (1997). Then $q_r$ is used to calculate the corresponding cloud water $q_c$ according to the reversed Kessler scheme. We assumed that moisture is conserved during one time step and oversaturation is not allowed. In the model, $q_c$ can be converted to the associated $q_v$ according to the saturation adjustment processes described by Soong and Ogura (1973) and Klemp and Wilhelmson (1978). The calculated $q_v$ is used to update the model background. Satellite retrieved rain rates also can be assimilated in the model using a similar scheme. Detailed descriptions for the RK-nudging method can be found in Chapter 5.

8.3.2 Nowcasting
In this chapter, the cross-correlation method was used to generate 1 h nowcasts for the nudging processes. At the first step, $n \times n$ arrays within the radar range are generated
at \((T - \delta t)\). Then the initial array is compared to all arrays (obtained at \(T\)) within the radius of a pre-defined searching area and the associated correlation coefficients are calculated. The direction from the selected array to the array with the highest correlation coefficient is adopted as the vector representing the movement of the selected array between \((T - \delta t)\) and \((T)\). By assuming the movement is not changed at subsequent times, we can forecast the future precipitation information over a short period ahead. Detailed descriptions about the cross-correlation based nowcasting can be found from Rinehart and Garvey (1978). In this paper, \(\delta t\) was set to 1 hour as for some certain weather systems, 2 h nowcasts may include considerable errors, and has the great possibility of providing less skill compared to the corresponding NWP simulations.

### 8.3.3 Model configurations

Same cases used in Chapter 5 are applied in this chapter. All cases were initialized using the previous 6 hours free forecasts from WRF. Observed radar reflectivity from the NZ National Radar Network was assimilated at \((T+0)\) for “Radar” experiments. Observed radar reflectivity and the associated “RainSat” analysis were assimilated within and out of the radar range, respectively for “Radar+RainSat”. For the experiments with the assimilation of nowcasting data (“Ext-Radar”), radar observed reflectivity was assimilated at \((T+0)\) as well and in addition, corresponding extrapolated radar reflectivity was assimilated at the lead time of 1 hour \((T+1)\). The merged analysis, which includes the both the observations and 1 hour extrapolated reflectivity and the “RainSat” analysis, was assimilated for the “Ext-Radar+RainSat” experiments. The experimental design is shown in Figure 8.2.

As we mentioned in Section 5.4 we did not update the backgrounds continuously with nudging for several reasons: (1) our computational resources did not support the assimilation of massive observations at high resolution. (2) We calibrated our radar data every hour and also (3) we simply assume that, the improvement from a “one-time” nudging test is a precondition for the further implementation of a
comprehensive system at the next step. The time window adopted in this chapter was 30 min, which means that the selection of a liquid only microphysics scheme in the nudging process was acceptable based by the studies by Wang et al. (2013).

8.4. Results and Discussions

8.4.1. Detailed case study

In this section, an example of the subjective evaluation for a heavy rainfall event occurred on 07 January 2012 is presented. For this case, a precipitation system commenced over the South Pacific Ocean at about 1500 UTC 06 January and gradually moved towards the North Island of New Zealand. The National Radar Network observed strong rainfall from about 2100 UTC 06 January in the region of the Northland. The main rain band moved across the North Island and resulted very serious flooding in the Lake Taupo and Tongariro region. The intensity of the precipitation system decreased after about 9 hours and moved out of the radar range from the east coast of Gisborne region. Figure 8.3 gives the Mean Sea Level Pressure (MSLP) manual analysis obtained at 18 UTC 06 January 2012, which was 6 hours before the assimilation time window. We find that the north of New Zealand was controlled by a low pressure system and then this low pressure centre moved southward (figure not shown) and affected almost the entire North Island for the next 24 hours.

For observation assimilation experiments, radar observed reflectivity and the “RainSat” retrieved rain rates were assimilated at 0000 UTC 07 January 2012 with the time window of 30 minutes. For the nowcast assimilation experiments, besides the observations, 1 h extrapolated radar reflectivity and the “RainSat” analysis were nudged into the model at 0100 UTC 07 January. For this case, 1 hour nowcast was generated based on the information obtained at 23 UTC 06 January and 00 UTC 07 January. Verifications were carried out from 01 UTC 07 January using the calibrated 1 h radar rainfall accumulation as the "truth field ".

106
Figure 8.4 gives the comparisons of different data assimilation schemes and the associated observations obtained from 0200 UTC (1 h after the nowcasting data assimilation) to 0400 UTC. We can see that the “Control” experiments apparently underestimated the precipitation for the entire 3 hours. Moreover, the simulated main rain band was located on the east side to the observed one. The assimilation of radar observed reflectivity (“Radar”) did not provide obvious adjustments in the regard, while we find that the precipitation was strengthened in the area along the west coast of the Northland region and Auckland. For “Radar+RainSat”, more accurate precipitation estimates were produced. It is apparent that the simulated precipitation along the east coast of Northland was suppressed, while those along the west coast were slightly strengthened overall. For all the observation assimilation experiments, simulated precipitation areas were largely underestimated compared to the associated radar observations, especially in the central North Island and the region along the west coast.

In order to prolong the effects of the initial conditions and make further adjustments on the model backgrounds, 1 hour nowcasts were assimilated into the model. We can easily find that “Ext-Radar”, which with the assimilation of both the observations and extrapolated data, provided better simulations compared to the assimilation of the observations alone. At 02 UTC, the main rain band has been adjusted well while for the next 2 hours, the effects of the incorporated nowcasts reduced and the forecasts were very similar to the ones obtained from “Radar+RainSat”. The extreme right column in Figure 8.4 shows the results obtained from the assimilation of both the observed/extrapolated reflectivity and “RainSat”. It is apparent that “Ext-Radar+RainSat” provided the highest skill compared to all other data assimilation schemes. At 02 UTC, “Ext-Radar+RainSat” provided moderate precipitation in the central North Island, although the rainfall area was still underestimated compared to the radar observations. More reasonable precipitation forecasts were also provided along the west coast. It is clear that, by the assimilation of nowcasting data, the
location of the main rain band has been well adjusted from the east coast to the Northland region. At 03 UTC, we find that the precipitation along the west coast and in the region of Tongariro National Park still could not be adequately represented. But compared to other schemes, “Ext-Radar+RainSat” still gave the most reasonable simulations in such areas. For example, compared to “Ext-Radar”, precipitation was estimated well in the region near Cape Reinga, although the intensity was overestimated. “Ext-Radar+RainSat” also generated heavier precipitation in the region of New Plymouth compared to all other schemes, which agreed with the associated observations. At 04 UTC, the effects of the assimilation of extrapolated reflectivity and the “RainSat” analysis were still very significant. For example, the simulation along the west coast apparently had higher skill relative to the ones in other places. However, we find that, in the North Island, the precipitation was still largely underestimated, while the observed precipitation had already moved southward and affected Palmerston North at 0400 UTC.

Figure 8.5 shows the 3 h rainfall accumulations in terms of different data assimilation schemes. We can see that, compared to the radar accumulation, similar to the studies for Figure 8.4, the precipitation was underestimated by all schemes adopted in this chapter. In general, “Radar” generated very similar results to “Control”, while very slight improvements were made by “Radar” in the area along the west coast of Northland and Auckland. “Radar+RainSat” provided higher skill compared to “Radar” as more reasonable precipitation was presented near the Waikato region and along the west coast of the North Island. The assimilation of nowcasts has the capability of providing moderate improvements for this case as “Ext-Radar+RainSat” gave the highest skill with wider simulated precipitation coverage over the central North Island. However, it is worth noting that none of data assimilation schemes generated the precipitation core very well. From the observations, we see that the core located in the area between Auckland and New Plymouth, while for most data assimilation schemes, the cores of precipitation were predicted in Auckland, which is about 100 km away from the observed one.
Figure 8.6 shows the 9 hours objective evaluations from 01 UTC in terms of different scores and thresholds (0.2 \text{ mm h}^{-1}, 0.5 \text{ mm h}^{-1}, 1.0 \text{ mm h}^{-1}, 2.0 \text{ mm h}^{-1} and 5.0 \text{ mm h}^{-1}). Forecasts and observations were resampled at the same spatial resolution of 3.0 km. From POD statistics, we find that “Control” provided the lowest skill on average for all thresholds and “Ext-Radar+RainSat” gave the highest skill. “Ext-Radar” and “Radar+RainSat” provided very similar skills and they were both better than “Radar” on average, especially for a relatively large threshold (e.g., > 1.0 \text{ mm h}^{-1}). When the threshold increased to 5.0 \text{ mm h}^{-1}, very small POD scores were obtained (less than 0.4 in overall) and the improvements given by the assimilation of radar and satellite nowcasts became trivial.

In contrast to POD, “Radar+RainSat”, “Ext-Radar” and “Ext-Radar+RainSat” provided very similar results in FAR, which indicates that the assimilation of the “RainSat” based nowcasting data using the RK-nudging method has very limited capability in decreasing spurious precipitation. Highest FAR scores were presented by “Control” on average, especially for the relatively smaller threshold (e.g., less than 5.0 \text{ mm h}^{-1}). The assimilation of the observed reflectivity provided smaller FAR scores than “Control” while they were both higher than other data assimilation schemes on average. For the verifications at 5.0 \text{ mm h}^{-1}, very high FAR scores were obtained for all forecasts and the difference between different schemes were trivial.

ETS provides the combined analysis considering both “right” and “wrong” predictions. For the ETS statistics of this case, we find that, the main improvements led by the assimilation of satellite based nowcasts presented after 2-4 hours. Similar to POD and FAR statistics, “Ext-Radar” and “Radar+RainSat” provided very similar scores. “Radar” provided higher skill compared to “Control” but apparently, it was less competitive to other schemes used in this chapter. With the threshold increased,
the difference between different data assimilation schemes decreased and as above, very small scores were shown by all simulations when the threshold increased to 5.0 mm h\(^{-1}\).

According to both the subjective and objective evaluations, we find that, for this case, the assimilation of 1 h nowcasts has the capability of prolonging the effects of the initial conditions and thus correcting the model background correspondingly. The simulated precipitation pattern was adjusted and improved by incorporating nowcasting data in the model compared to the associated observations. In addition, the effects of the assimilation last up to 9 hours approximately, while the effects were mainly shown at relatively small verification thresholds. Using a more advanced technique, like 4DVar or EnKF, might provide further improvement in the future.

### 8.4.2 Combined skill scores

A total of 13 rainfall cases occurred during the summer of 2011/2012 were selected to evaluate the effects of the assimilation for nowcasting data. Different skill scores, including POD, FAR, ETS, Correlation Coefficient and Fractional Skill Score (FSS) (Roberts and Lean, 2008), were applied to evaluate different forecast schemes. Similar to the last section, 1 hour calibrated radar accumulations were used to provide the “truth field” against NWP simulations. All verifications were carried out from the lead time of 1 hour, which was the time for assimilating nowcasting data and 1 hr after the assimilation of observations.

Figure 8.7 shows the combined POD, ETS and FAR scores over all selected cases. Different thresholds from 0.2 mm h\(^{-1}\) to 5.0 mm h\(^{-1}\) were applied. All verifications were carried out at the spatial resolution of 3 km, which was the same as the model spatial resolution adopted in this chapter. We find very similar results as Figure 8.6. For POD statistics, it is apparent that “Ext-Radar+RainSat” has the capability of providing the highest skill on average. “Radar+RainSat” and “Ext-Radar” provided
comparable skills, which were higher than the skill from the assimilation of radar reflectivity alone (“Radar”). For relatively small threshold (e.g., 0.2 mm h\(^{-1}\)), the biggest difference of POD between “Ext-Radar+RainSat” and “Control” was more than 0.25, while with the threshold increased, the improvement decreased and the biggest difference of POD was less than 0.15 when the threshold increased to 5.0 mm h\(^{-1}\).

FAR scores were very high for almost all simulations, especially for the relatively high thresholds. The smallest FAR was usually given by “Ext-Radar+RainSat” and the largest one was presented by “Control” on average. When the threshold was 0.2 mm h\(^{-1}\), The smallest FAR was about 0.6, while it increased rapidly with threshold increased (e.g., 0.72, 0.8, 0.85 and 0.9 for the threshold of 0.5 mm h\(^{-1}\), 1.0 mm h\(^{-1}\), 2.0 mm h\(^{-1}\) and 5.0 mm h\(^{-1}\), respectively). In contrast to POD statistics, for the threshold less than 2.0 mm h\(^{-1}\), it is apparent that “Ext-Radar” slightly outperformed “Radar+RainSat” while when the threshold increased to 5.0 mm h\(^{-1}\), almost all schemes generated similar skills.

We can see low ETS scores on average in this chapter, and there are several reasons leading to that. First, the model usually has limited capability of representing the nonlinear high impact weather systems. Second, the high verification resolution (3 km) also made a large contribution to the relatively low scores in this chapter. However, we can still find that “Ext-Radar+RainSat” outperformed others on average. “Control” provided the lowest skill but the difference between “Ext-Radar+RainSat” and “Control” could be very small for large verification threshold. For example, for the threshold of 0.2 mm h\(^{-1}\), the ETS scores at the lead time of 3 hr for “Ext-Radar+RainSat”, “Ext-Radar”, “Radar+RainSat”, “Radar” and “Control” were about 0.23, 0.18, 0.18, 0.15 and 0.13, respectively. While with the threshold increased to
2.0 mm h⁻¹, the scores decreased considerably and it is apparent that the difference between the highest skill and lowest skill was trivial. In addition, from all above skill scores, we find that, no matter what type of data incorporated, the adjustments caused by the RK-nudging approach only last about 9 hours on average, which is similar to the scores obtained from the detailed case studies presented in the last section.

Figure 8.8 shows the calculated correlation coefficients for different schemes, here we added the skill score of nowcasting as a reference. We find that, from the point-by-point quantitative comparisons, as our expectation, nowcasting showed the highest skill at (T+1), and “Ext-Radar+RainSat” still provided much higher skill compared to “Radar+RainSat”, and “Ext-Radar” had higher score compared to “Radar” on average. This indicates that, from the viewpoint of correlation coefficient, the assimilation of nowcasting data indeed had the capability of improving model background significantly at a lead time of 1 h (although it still could not outperform the traditional extrapolated based nowcasting) and introduced positive effects on the following precipitation forecasts. All data assimilation schemes showed higher skills than “Control” in general, and the improvements last up to about 9 hours on average in the cross-correlation based statistics. In addition, as the analyses for Figure 8.7, “Radar+RainSat” and “Ext-Radar” showed comparable skills, especially after 3 hours, which indicates that the assimilation of observed satellite information out of the radar range may have similar impacts to the assimilation of the 1 hour radar based nowcast in New Zealand.

Figure 8.9 shows FSS scores for different data assimilation schemes at different spatial scales from 3 km to 150 km. It is apparent that for the first about 6 hours, the differences between different schemes were obvious, especially for relatively small threshold. Not unexpectedly, nowcasting still showed the highest skill for the first 1 h, although the skill decreased rapidly after that, and for T+3h, all NWP schemes outperformed nowcasting. Among NWP schemes, At the lead time of 1 hr, for the
threshold less than or equal to 2.0 mm h\(^{-1}\), “Radar” and “Ext-Radar” provided very similar results. In contrast, “Radar+RainSat” and “Ext-Radar+RainSat” provided slightly higher skill for relatively small spatial scales but the difference between “Radar” (“Ext-Radar”) and “Radar+RainSat” (“Ext-Radar+RainSat”) reduced as the verification scale increased. For the threshold of 5.0 mm h\(^{-1}\), all data assimilation schemes provided almost the same skills on average. At the lead time of 2 h, it is apparent that “Radar+RainSat”, “Ext-Radar” and “Ext-Radar+RainSat” have higher skills compared to the assimilation of the observed reflectivity alone. One hour later (lead time = 3 h), “Ext-Radar+RainSat” outperformed other schemes for the verification thresholds less than 5.0 mm h\(^{-1}\). “Ext-Radar” and “Radar+RainSat” have similar skills and both of them performed better than “Radar”.”Control” still gave the lowest skill in general. However, for the threshold of 5.0 mm h\(^{-1}\), there was no big difference between different assimilation schemes. At the lead time of 6 hr, the advantage of “Ext-Radar+RainSat” was more obvious. Followed by the skill of “Radar+RainSat”, which was slightly better than “Ext-Radar”. The effects of the observed reflectivity assimilation already became trivial. For high threshold like 5.0 mm h\(^{-1}\), “Ext-Radar+RainSat” showed more obvious improvements, especially for relatively large verification scales. Other schemes provided very similar, or even slightly worse results compared to “Control”. At the lead time of 9 hr, we can see that the average forecast skill was decreased gradually. “Ext-Radar+Rainsat” still provided the highest skill on average, while the effects of assimilation with other schemes became very small. It is worth noting that, when the threshold increased to 5.0 mm h\(^{-1}\), the combined FSS became very small for all adopted schemes, which indicates that the capability of improving heavy rainfall forecasts was limited, even when the model was initialized with prolonged and improved initial nowcast conditions.

According to the above statistics, we can see that the assimilation of nowcasting data
has the capability of improving precipitation forecasting further compared to the “one
time” reflectivity assimilation schemes. This is similar to the results provided by
Sokol and Zacharov (2012). However, we also noticed that, even with the assimilation
of “observation + nowcast”, the combined skill for precipitation forecast was still
relatively low (e.g., compared with the skill of the nowcasting at T+1). There are
several reasons leading to that, including: (1) Clouds and precipitation are
discontinuous and are usually formed by complex nonlinear processes and thus they
are very difficult to be modelled well. (2) Although we incorporated high resolution
rainfall estimates in the model, there are significant errors existing in the RK-nudging
method (see Section 5.5). Also, a continuous nudging scheme may improve the
forecast further given the computational resources were sufficient. (3) The quality
control processes for radar reflectivity and the “RainSat” analysis might lead to
additional uncertainties during the nudging processes. (4) It is apparent that the
accuracy of the precipitation forecasting described in this chapter depends on the
accuracy of the nowcasting technique. (5) last but not the least, a good precipitation
forecasting is really dependant on a general high quality model background. However,
in this chapter, we only incorporated high resolution radar and satellite precipitation
analyses which were inconsistent with other model fields, and could introduce
significant imbalances, consequently, the effects of assimilation decreased fast.

8.5. Conclusions

This chapter investigated the effects of the assimilation with nowcasting data in New
Zealand. 13 relatively heavy rain cases were selected to evaluate different data
assimilation schemes. The RK-nudging approach was selected to incorporate data into
the model with the time window of 30 min. The cross-correlation method was
adopted in this chapter for providing 1 h nowcasts.

According to both the subjective and objective evaluations, we can conclude that the
assimilation of 1 h nowcasts has the capability of improving precipitation forecasting
compared to the assimilation of observations alone. In general, “Ext-Radar+RainSat” provided the highest skill compared to other schemes, which indicates that although there are significant errors inherent in the “RainSat” technique and the cross-correlation method, the advantage of assimilating satellite based nowcasting data was capable of offsetting the uncertainties introduced in the model overall.

“Ext-Radar” and “Radar+RainSat” produced similar skills on average and both of them have higher skills compared to the traditional observed radar reflectivity assimilation. This indicates that by the assimilation of rainfall information beyond the radar range, better estimates of precipitation evolution could be achieved, and the improvement was comparable to the assimilation of radar based 1 h nowcasts, especially after about 3 hours.
9. Conclusions

In this thesis, we explored the possibilities of using nowcasting and NWP based approaches to improve (very) short range precipitation forecasting in New Zealand. The thesis presents the evaluation of clouds/precipitation assimilation schemes that might be useful in New Zealand, or other similar countries that have limited computational resources available. As New Zealand is an island country, which is surrounded by oceans, we also investigated the possibility of using the satellite based approach for providing precipitation estimates over the Tasman Sea, and improving the traditional radar based nowcasting and data assimilation technique.

First, we implemented the “RainSat” technique for delineating precipitation over the Tasman Sea, where most high impact weather systems initiate and develop. Visible and infrared data obtained from GOES every 30 minutes were applied to provide bi-frequency distribution statistics corresponding to ground based observations (radar). A scheme was designed to determine the optimal rainfall probability threshold automatically according to the weighting function calculated within the radar range. The “RainSat” based nowcasting scheme was developed and evaluated, and the results showed that the “RainSat” based scheme has the capability of generating reliable 0-2 h precipitation forecasts while after 2 hours, the precipitation area would be significantly underestimated due to the decreased size of VIS/IR bi-frequency distributions. In addition, the successful implementation of the “RainSat” approach for New Zealand makes the “RainSat” based NWP initialization scheme a possible next step.

Although the “RainSat” type techniques have been widely used in many countries before, the errors inherent in the technique have not been extensively investigated. In the thesis we investigated four main errors/uncertainties which might have significant effects on the skill of the “RainSat” analysis: (1) Different weather systems in different locations are expected to have different VIS/IR distributions, while for the
“RainSat” technique, rainfall is estimated based on the VIS/IR distributions obtained within the radar range, which suggests that there may be significant additional errors in precipitation estimates in areas far away from the radar coverage. We used a single radar to generate the “RainSat” analysis over all of New Zealand and data from other radars were used to verify the results. According to the objective evaluations, the skill of the “RainSat” technique gets poorer with the distance between radar and the verification grid point increased to about 400.0 km. For the “RainSat” based nowcasting, the “regression issue” mainly dominated the forecast time range from 0 to 2 hours, after that, the errors inherent in the extrapolation approach and the weather system characteristics play a more essential role (usually relatively poor performance of the nowcasting is produced over almost the entire area of interest after 2 hours). (2) The low spatial resolution of satellite data may also introduce uncertainties in the performance of the “RainSat” technique. However, it is not as significant as the effects of the “regression issue”. The statistics showed that low resolution satellite data have a better capability of yielding relatively better precipitation estimates. In the “RainSat” based nowcasting, the differences produced by different spatial resolutions of satellite data were less than 10%, which was much smaller compared to the spatial sampling uncertainties inherent in the radar data based experiments. It is appropriate to say that the spatial scale of the satellite data is not a dominant contributor to the skill of the “RainSat” technique and the associated nowcasting. (3) In addition, there are significant errors inherent in the determination of the height for the “RainSat” analysis, since the “RainSat” technique estimates precipitation based on the VIS/IR data obtained at the cloud top height (CTH) and the reflectivity observed at the radar echo top height (ETH). The statistics showed that within the range of 50 km of the radar station, the height difference between ETH and CTH could be larger than 5.0 km while the difference decreased with the distance between analysis point and the radar station increased. In the thesis, we adopted the Effective Height (EH), which is the average of CTH and ETH, as the “RainSat” analysis height. But it is worth noting that the error still exists when we use the “RainSat” analysis to initialize the NWP model, especially if the model has high resolution vertical configurations. (4) We also
investigated the errors inherent in the rainfall intensity estimates using the “RainSat” technique. Compared to the traditional method, for example, applying the average radar retrieved rain rates to the “RainSat” probability map, the new method, which determines the rain rates based on the different initial thresholds of radar data, has the capability of providing slightly higher skill for relatively intense precipitation and yielding similar results for wide spread and moderate/light rainfall. Overall, for both methods, within the range of “ground truth” (e.g., NZ National Radar Network), precipitation amounts were more likely to be overestimated, while over the Tasman Sea (verifications were carried out against TMPA analyses), the “RainSat” technique had a higher probability of providing smaller rain rates.

In order to reduce the errors in the estimates of cloud motion vector and precipitation area for the extrapolation based nowcasting, especially in the area near the edge of the radar range, the “RainSat” analysis was merged with radar data to extend the availability of precipitation delineation. An automatic system was designed to provide the precipitation nowcasting based on the “radar+RainSat” combined analysis. According to both the subjective and objective evaluations, it is apparent that the combined analysis has the capability of reducing the biases for the estimates of reflectivity-weighted echo centre and precipitation area significantly compared to the traditional radar alone based nowcasting. Based on the statistics of POD, ETS, FAR and FBi, the merged analysis provided higher skill scores, especially after 2-3 hours on average. However, it is still worth mentioning that, largely due to the poor performance of the “RainSat” technique on the estimates of rainfall intensity, the combined analysis was still not capable of providing obvious improvements for the nowcasting of strong and small cells.

In order to use radar reflectivity and the “RainSat” analysis to initialize the NWP model, we developed a data assimilation scheme based on the Kessler warm rain scheme in a reverse order, and the associated saturation adjustments (RK-nudging). Compared to the WRF 3D-Var reflectivity forward operator, the new developed
scheme reduced the errors caused by the linearization approximation. In addition, the RK-nudging scheme works well in the dry grid point, while for the traditional LHN scheme, the moisture fields in the dry grid are requested to be borrowed from the nearest wet grid point, which may lead to significant errors, especially for narrow rain bands. A total of 13 heavy rainfall cases occurred during the summer of 2011/2012 in New Zealand were employed to investigate the RK-nudging scheme. The verifications showed that the scheme has the capability of improving precipitation forecast up to 7-9 hours on average, while the improvements decreased rapidly with the verification threshold or forecast lead hours increased.

The skill of the RK-nudging approach with different model cloud physics schemes, besides the Kessler scheme (KS), including LS, Eta, W3 and W5, were investigated. The effects of the RK-nudging approach on the simulations of temperature, winds and precipitation were all evaluated. Different objective scores like POD, FAR, ETS and FBI were applied and the results showed that, for precipitation forecasting, LS provided the highest skill on average and the Eta scheme have the lowest scores. The difference between the highest skill and lowest skill increased with the verification threshold increased. For temperature simulation, different microphysics schemes led to moderate difference. Overall, Eta generated the highest temperature and KS estimated the temperature less than the others on average. Generally, WRF was capable of providing satisfactory temperature simulations. In contrast, the difference produced by the use of different microphysics schemes were trivial for winds, which indicates that the assimilation of rain rates was not capable of providing obvious adjustments in wind fields and a separate winds assimilation scheme is still required for New Zealand.

Considering that New Zealand is an island country and that most high impact weather systems initiate and develop over the Tasman Sea, where there are no radar data, it is essential to use satellite data to initialize the model before the weather system actually starts affecting New Zealand. In the thesis, we investigated the effects of the
assimilation of clouds/precipitation data retrieved from satellite in the area out of the radar range. Precipitating clouds were assimilated using the WVC approach, and satellite retrieved rain rates and the radar observed reflectivity were assimilated using both the RK-nudging method and the WVC approach. The results showed that, the assimilation of “reflectivity+RainSat” using the RK-nudging scheme provided the highest skill for the first 0-4 hours forecasts while after that the scheme of “reflectivity+clouds” might outperform the other schemes tested in the thesis. This indicates that the incorporation of clouds/precipitation data has the capability of improving the precipitation forecasting in New Zealand compared to the radar alone assimilation. In addition, the new developed RK-nudging method provided higher skill compared to the use of the WVC approach for the selected cases, which was mainly caused by the reduced representativeness of the empirical coefficients adopted for our WVC experiments.

In order to improve the precipitation forecasting further by adjusting the model background better, we applied the 1 h nowcasts to modify the model fields. The cross correlation technique was used to generate both the radar and the combined (“radar+RainSat”) nowcasts. By using the RK-nudging approach, the nowcasting data (or the observed rain rates) were assimilated in the model at the lead time of 1 h. Different objective statistical scores, including POD, ETS, FAR and FSS, showed that better precipitation forecasts were achieved by the assimilation of both the observed and extrapolated radar reflectivity and “RainSat”. The assimilation of the observed and extrapolated radar reflectivity generated comparable skill to the assimilation of both the observed radar reflectivity and the "RainSat" analysis together, which indicates that the assimilation of clouds/precipitation out of the radar range might be able to provide similar effects as the adjustment made by the radar alone nowcasting data in the model. It is worthwhile to mention that, the assimilation of extrapolation based nowcasts was still not capable of adjusting the pattern and intensity for strong small cells, especially when the verification was carried out at high spatial resolution. Due to the limitation of the available computational resources, limited number of
selected heavy rainfall cases was investigated in our NWP experiments. In order to
give a full evaluation of different data assimilation schemes in New Zealand, it is
apparent that more cases studies are essential. It is hoped that this investigation will
be carried out in the future subject to the improved availability of local computational
resources.

Overall, the thesis investigated the possibility of implementing high resolution
clouds/precipitation assimilation scheme in a numerical weather forecasting system in
New Zealand, and presented the preliminary results of the assimilation experiments.
Unlike other countries like UK, US or Japan, New Zealand may not have sufficient
computational resources for very high resolution 4D-Var data assimilation for the
next several years. Thus the precipitation estimation/nowcasting approaches, and the
data assimilation schemes proposed in this thesis which use the relatively
straightforward nudging approach, show great potential to be applied in New Zealand,
or other similar countries which are not equipped with very powerful computational
facilitates.
Appendix A. Verification Skill Scores

Forecasts from the NWP model and the “RainSat” analysis can be evaluated using different objective skill scores. Here we give the equations of calculating the skill scores used in this thesis. It is worthwhile to mention that, when calculated the combined scores over a range of cases, we produced a case pool first and applied the entire data pool in the verification system. This method may suppress the statistical instability by reducing the weighting of the individual cases with outstanding skill scores. However, we might risk underestimating the features of individual cases if we try to understand them further.


<table>
<thead>
<tr>
<th>Table A.1: Categorical contingency table for ratio based scores</th>
</tr>
</thead>
<tbody>
<tr>
<td>Observed</td>
</tr>
<tr>
<td>Forecast</td>
</tr>
<tr>
<td></td>
</tr>
</tbody>
</table>

\[ N = total \]

1. The probability of detection (POD):

\[ POD = \frac{hits}{hits + misses} \quad (A.1) \]

2. The equitable threat score (ETS):

\[ ETS = \frac{hits - hits_r}{hits + misses + false alarms - hits_r} \quad (A.2) \]

where \[ hits_r = \frac{(hits + misses)(hits + false alarms)}{N} \]

3. The Critical Success Index (CSI):
Appendix A. Verification Skill Scores

\[ CSI = \frac{\text{hits}}{\text{hits} + \text{misses} + \text{false alarms}} \]  
(A.3)

(4) The Root Mean Square Error (RMSE), compared to MAE, RMSE shows greater influence on large errors

\[ RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (F_i - O_i)^2} \]  
(A.4)

(5) The Mean Absolute Error (MAE)

\[ MAE = \frac{1}{N} \sum_{i=1}^{N} |F_i - O_i| \]  
(A.5)

(6) The Correlation Coefficient (CC)

\[ CC = \frac{\sum (F - \bar{F})(O - \bar{O})}{\sqrt{\sum (F - \bar{F})^2} \sqrt{\sum (O - \bar{O})^2}} \]  
(A.6)

(7) The Fractional Skill Score (FSS)

\[ FSS = 1 - \frac{MSE_n}{MSE_{n(ref)}} \]  
(A.7)

Where \( MSE_{n} \) at the neighborhood length \( n \) can be represented as:

\[ MSE_{n(ref)} = \frac{1}{N_x N_y} \sum_{i=1}^{N_x} \sum_{j=1}^{N_y} \left[ \sum_{i=1}^{N_x} \sum_{j=1}^{N_y} O_{n(i,j)}^2 + \sum_{i=1}^{N_x} \sum_{j=1}^{N_y} M_{n(i,j)}^2 \right] \]  
(A.8)

\[ MSE_n = \frac{1}{N_x N_y} \sum_{i=1}^{N_x} \sum_{j=1}^{N_y} [O_{n(i,j)} - O_{n(i,j)}]^2 \]

Where

\[ O_{n(i,j)} = \frac{1}{n^2} \sum_{k=1}^{n} \sum_{l=1}^{n} I_o[i + k - 1 - \frac{(n-1)}{2}, j + l - 1 - \frac{(n-1)}{2}] \]

\[ M_{n(i,j)} = \frac{1}{n^2} \sum_{k=1}^{n} \sum_{l=1}^{n} I_m[i + k - 1 - \frac{(n-1)}{2}, j + l - 1 - \frac{(n-1)}{2}] \]  
(A.9)

\( I_o \) and \( I_m \) are the binary fields for radar observed (\( O_o \)) and forecast rainfall (\( M_o \)).
fields at the threshold $q$:

$$I_o = \begin{cases} 1 & (O_r \geq q) \\ 0 & (O_r < q) \end{cases}$$

$$I_M = \begin{cases} 1 & (M_r \geq q) \\ M & (M_r < q) \end{cases}$$

(A.10)
Appendix B. Details of the implementation of the RK-nudging codes in WRF

In order to implement the RK-nudging scheme in WRF, many changes are required to be made in different WRF programs. Figure B.1 gives an illustration about where the RK-nudging codes located under the architecture of WRF. Apparently, the core codes of the RK-nudging are under the program of errob. The main purpose of errob is to obtain the difference between the model diagnostics and the related observations and apply the relaxation function to the corresponding bias. It comes with the functions such as module_fddaobs_rtfdda.F, which is main module for observation nudging (FDDA module). Detailed information about the implementation of FDDA module can be found from Liu et al. (2005, 2006). The program of errob is called by the program module_fddaobs_driver. It is worthwhile to note that both the model and observation fields are required to be spatially interpolated before any nudging activities.

The program module_fddaobs_driver is called by module_first_rk_step_part2 under the dyn_em, which is the dynamic core of WRF-ARW. It is worthwhile to note that, in order to run the module RK-nudging properly, there are a lot of additional fields which are expected to be passed from/to module_first_rk_step_part2, including density of air, cloud water mixing ratio, rain water mixing ratio etc., and all of them are required to be added to related functions.
Appendix B. Details of the implementation of the RK-nudging codes in WRF

The program of wrf_fddaobs_in controls the observation and model preprocessing. Note that in WRF FDDA, observations are read and stored in column basis, which means that all the data are read in a column called varobs, which comes with two dimensions, one is the data type and another one represents the number of observations. Here we added our own data type (e.g., radar reflectivity) by extending the variable dimension of varobs.

Due to the limitation of pages in the thesis, here we only gives the codes of the RK-nudging scheme implemented in errob, which are applied to calculate the moisture bias between the postprocessed observations and model fields. Different versions of WRF may require different entry fields for this function, the codes listed here were developed based on WRF 3.4.1:

......
Appendix B. Details of the implementation of the RK-nudging codes in WRF

! REVERSE KESSLER WARM RAIN SCHEME ~ MOISTURE ERROR
! ~ implemented by Sijin Zhang 11 July 2013 and 3 Sep 2013
! Version 1.0: 11 July 2013
! Version 1.0.1: 25 July 2013
! Version 1.0.2: 13 August 2013
! Version 2.0: 3 Sep 2013
!
!
write(*,*) 'ASSIMILATED VALUE IS: ', VAROBS(4,n)
if((VAROBS(4,n).gt.10.0).and.(VAROBS(4,n).le.55.0)) then
    cp = 1004.5
    xlv = 2.5e+06
    svpt0 = 273.15
    svp1 = 0.66112
    svp2 = 17.67
    svp3 = 29.65
    ep2 = 0.62175
    f5 = svp2*(svpt0-svp3)*xlv/cp
    pressure = 1.0000e+05 * (pii(IOB,KOB,JOB)**(1004./287.))
    temp = pii(IOB,KOB,JOB)*th(IOB,KOB,JOB)
    es = 1000.0*svp1*exp(svp2*(temp-svpt0)/(temp-svp3))
    qvs = ep2*es/(pressure-es)
R = (1+pressure/(pressure-es)*qvs*f5/(temp-svp3)**2.0);

if(VAROBS(4,n).gt.2.0) then
    qr_obs = (10**(VAROBS(4,n)-43.1)/17.5)/rho(IOB,KOB,JOB)
    qr_obs = qr_obs/1000
else
    qr_obs = 0.0
endif

write(*,*) 'CURRENT QR_OBS IS: ', qr_obs
write(*,*) 'CURRENT BK QRB IS: ', qrb(IOB,KOB,JOB)
delta_qr = qr_obs - qrb(IOB,KOB,JOB)
if(delta_qr>0) then
delta_qc = MAX((delta_qr + 0.001*0.001*dt + Erdt)/(0.001*dt + 2.2*dt*qrb(IOB,KOB,JOB)**(0.875)),0.0)

delta_qv = (delta_qc - R*qvb(IOB,KOB,JOB) + R*qvs)/R;
endif
if(delta_qr<0) then
  if(qr_obs>0) then
    delta_qc = MIN((delta_qr + 0.001*0.001*dt + Erdt)/(0.001*dt + 2.2*dt*qrb(IOB,KOB,JOB)**(0.875)),0.0)
    delta_qv = (delta_qc - R*qvb(IOB,KOB,JOB) + R*qvs)/R;
    if(delta_qv>0) then
      delta_qv = 0
    endif
  endif
endif
if(delta_qr.eq.0) then
  delta_qv = 0
endif
qv_update = qvb(IOB,KOB,JOB) + delta_qv
if(delta_qv.ne.0) then
  ERRF(4,N)=ERRF(4,N)+qv_update-((1.-DZOB)*((1.-DyOB)*((1.-DxOB)*QVB(IOB,KOB,JOB)+DxOB*QVB(IOB+1,KOB,JOB))+DyOB*((1.-DxOB)*QVB(IOB,KOB,JOB+1)+DxOB*QVB(IOB+1,KOB,JOB+1)))+DZOB*((1.-DyOB)*((1.-DxOB)*QVB(IOB,KOBP,JOB)+DxOB*QVB(IOB+1,KOBP,JOB))+DyOB*((1.-DxOB)*(QVB(IOB+1,KOBP,JOB)+DxOB*QVB(IOB+1,KOBP,JOB+1))))
else
  ERRF(4,N) = 0
endif
write(*,*) '***********************************************************************'
write(*,*) 'CURRENT OBS NO. : ', N
Appendix B. Details of the implementation of the RK-nudging codes in WRF

write(*,*),'CURRENT PROCESSING loc: (' , IOB, ' , KOB, ' , JOB, ' ): model background is: ', qvb(IOB,KOB,JOB), ', increment is: ', delta_qv
write(*,*),'NUDGED QV is: ', qv_update
write(*,*),'UPDATED ERRF IS: ', ERRF(4,N)
write(*,*),'****************************************************'
endif

...
Bibliography


Hagen, M. and S. E. Yuter, 2003: Relations between radar reflectivity, liquid-water content, and rainfall rate during the map sop. Quarterly Journal of the Royal Meteorological Society,


Jones, C. and B. Macpherson, 1997: A latent heat nudging scheme for the assimilation of


Ligda, M., 1953: The horizontal motion of small precipitation areas as observed by radar, Vol. 21, 60. Massachusetts Institute of Technology, Massachusetts.


Weather Review, 124 (8), 1746–1766.


Rogers, E., T. Black, B. Ferrier, Y. Lin, D. Parrish, and G. DiMego, 2001: Changes to the NCEP meso eta analysis and forecast system: Increase in resolution, new cloud microphysics, modified precipitation assimilation, modified 3dvar analysis. NOAA.


Sokol, Z., 2011: Assimilation of extrapolated radar reflectivity into a NWP model and its impact on a precipitation forecast at high resolution. Atmospheric Research, 100 (2-3), 201–212.


reflectivity with WRF 3d-var and its impact on prediction of four summertime convective events. Journal of Applied Meteorology and Climatology, 52 (4), 889–902.


Yeh, K. S., J. Cote, S. Gravel, A. Methot, A. Patoine, M. Roch, and A. Staniforth, 2002: The CMC-MRB global environmental multiscale (gem) model. Part iii: Nonhydrostatic


List of Tables:

Table 1.1: Short summary of NWP models (and data assimilation schemes) used operationally (Bauer et al., 2011)

<table>
<thead>
<tr>
<th>NWP centre</th>
<th>JMA</th>
<th>ECMWF Environment Canada</th>
<th>Meteo-France</th>
<th>Met Office</th>
<th>NCEP</th>
<th>GFS, NAM and WRF</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Models</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Model name</td>
<td>GSM, MSM</td>
<td>IFS</td>
<td>GEM</td>
<td>ARPEGE , AROME</td>
<td>UM</td>
<td></td>
</tr>
<tr>
<td>Global resolution</td>
<td>20 km / 60 levels</td>
<td>16 km / 91 levels</td>
<td>33 km / 80 levels</td>
<td>10-60 km / 70 levels</td>
<td>25 km (17 km) / 70 levels</td>
<td>32-110 km / 64 levels</td>
</tr>
<tr>
<td>Regional resolution</td>
<td>5 km (outer loop)</td>
<td>N/A</td>
<td>N/A</td>
<td>2.5 km</td>
<td>UKV: 1.5 km variable resolution</td>
<td>12 km</td>
</tr>
<tr>
<td><strong>Cloud / precipitation DA scheme</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Global scheme</td>
<td>4D-Var</td>
<td>4D-Var</td>
<td>4D-Var</td>
<td>4D-Var</td>
<td>4D-Var</td>
<td>3D-Var</td>
</tr>
<tr>
<td>Regional scheme</td>
<td>4D-Var</td>
<td>N/A</td>
<td>3D-Var</td>
<td>1D + 3D-Var</td>
<td>3D-Var + nudging</td>
<td>3D-Var</td>
</tr>
<tr>
<td><strong>Cloud/precipitation data assimilated</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Global scale</td>
<td>AMSR-E/TMI retrieved precipitation</td>
<td>HIRS/AIRS/IASI radiances, SSMI(S)/AMS R- E/TMI radiances etc.</td>
<td>N/A</td>
<td>AIRS/IASI</td>
<td>AIRS/IASI / cloudy radiances, AMSU-A</td>
<td>TMI retrieved precipitation</td>
</tr>
<tr>
<td>Regional scale</td>
<td>Radar</td>
<td>N/A</td>
<td>N/A</td>
<td>Radar</td>
<td>Radar/Clo ud fraction</td>
<td>N/A</td>
</tr>
</tbody>
</table>

*Currently, there is no high resolution precipitating clouds/precipitation assimilation scheme adopted in New Zealand operationally*
Table 1.2: Typical Z-R relationship recommended for WSR-88D

<table>
<thead>
<tr>
<th>Name</th>
<th>Relationship</th>
<th>Optimum for:</th>
</tr>
</thead>
<tbody>
<tr>
<td>Marshall-Palmer</td>
<td>$Z=200R^{1.6}$</td>
<td>General stratiform precipitation</td>
</tr>
<tr>
<td>WSR-88D Convective</td>
<td>$Z=300R^{1.4}$</td>
<td>Summer deep convection (non-tropical convection)</td>
</tr>
<tr>
<td>Rosenfeld</td>
<td>$Z=250R^{1.2}$</td>
<td>Tropical convection systems</td>
</tr>
<tr>
<td>East-Cook Stratiform</td>
<td>$Z=130R^{2.0}$</td>
<td>Winter stratiform precipitation in the US (east of continental divide)</td>
</tr>
<tr>
<td>West-Cook Stratiform</td>
<td>$Z=75R^{2.0}$</td>
<td>Winter stratiform precipitation in the US (west of continental divide)</td>
</tr>
</tbody>
</table>
Table 2.1: Summary of widely used satellites and the associated instruments for precipitation measurement (Kidd and Huffman, 2011)

<table>
<thead>
<tr>
<th>Instrument</th>
<th>Satellite</th>
<th>Ch.(S)</th>
<th>Bands</th>
<th>Res. (km)</th>
<th>Sampling</th>
</tr>
</thead>
<tbody>
<tr>
<td>SEVIRI</td>
<td>MSG</td>
<td>11</td>
<td>VIS-IR</td>
<td>1-3</td>
<td>15 min</td>
</tr>
<tr>
<td>GOES imager</td>
<td>GOES</td>
<td>5</td>
<td>VIS-IR</td>
<td>1-4</td>
<td>30 min</td>
</tr>
<tr>
<td>AVHRR</td>
<td>NOAA/MetOP</td>
<td>5</td>
<td>VIS-IR</td>
<td>1</td>
<td>Twice daily</td>
</tr>
<tr>
<td>MODIS</td>
<td>Aqua/Terra</td>
<td>36</td>
<td>VIS-IR</td>
<td>0.25-1</td>
<td>Twice daily</td>
</tr>
<tr>
<td>SSM/I</td>
<td>DMSP</td>
<td>7</td>
<td>19-85 GHz</td>
<td>12.5-25</td>
<td>Twice daily</td>
</tr>
<tr>
<td>SSMIS</td>
<td>DMSP</td>
<td>11</td>
<td>19-183 GHz</td>
<td>13-45</td>
<td>Twice daily</td>
</tr>
<tr>
<td>TMI</td>
<td>TRMM</td>
<td>9</td>
<td>10-85 GHz</td>
<td>5-25</td>
<td>Twice 2 days</td>
</tr>
<tr>
<td>AMSU</td>
<td>NOAA/MetOP</td>
<td>5</td>
<td>23-183 GHz</td>
<td>20-50</td>
<td>Twice daily</td>
</tr>
<tr>
<td>MHS</td>
<td>NOAA/MetOP</td>
<td>5</td>
<td>90-190 GHz</td>
<td>17-50</td>
<td>Twice daily</td>
</tr>
<tr>
<td>AMSR</td>
<td>Aqua</td>
<td>12</td>
<td>6-85 GHz</td>
<td>5-25</td>
<td>Twice daily</td>
</tr>
<tr>
<td>PR</td>
<td>TRMM</td>
<td>1</td>
<td>13.6 GHz</td>
<td>5</td>
<td>Twice 3 days</td>
</tr>
<tr>
<td>CPR</td>
<td>CloudSat</td>
<td>1</td>
<td>94 GHz</td>
<td>1.4</td>
<td>Once 16 days</td>
</tr>
</tbody>
</table>
Table 2.2: Selected cases and associated daily accumulated rainfall (mm) observed by NZ NIWA/MetService

<table>
<thead>
<tr>
<th>Case number</th>
<th>Date</th>
<th>Daily accumulated rainfall (mm)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(d/m/y)</td>
<td>Auckland</td>
</tr>
<tr>
<td>1</td>
<td>01/11/2011</td>
<td>10.3</td>
</tr>
<tr>
<td>2</td>
<td>09/11/2011</td>
<td>1.0</td>
</tr>
<tr>
<td>3</td>
<td>20/11/2011</td>
<td>0.0</td>
</tr>
<tr>
<td>4</td>
<td>21/11/2011</td>
<td>0.2</td>
</tr>
<tr>
<td>5</td>
<td>04/12/2011</td>
<td>---</td>
</tr>
<tr>
<td>6</td>
<td>15/12/2011</td>
<td>19.8</td>
</tr>
<tr>
<td>7</td>
<td>29/12/2011</td>
<td>29.8</td>
</tr>
<tr>
<td>8</td>
<td>30/12/2011</td>
<td>36.8</td>
</tr>
<tr>
<td>9</td>
<td>31/12/2011</td>
<td>7.2</td>
</tr>
<tr>
<td>10</td>
<td>07/01/2012</td>
<td>26.0</td>
</tr>
<tr>
<td>11</td>
<td>08/01/2012</td>
<td>4.4</td>
</tr>
<tr>
<td>12</td>
<td>12/01/2012</td>
<td>4.6</td>
</tr>
<tr>
<td>13</td>
<td>15/01/2012</td>
<td>0.4</td>
</tr>
</tbody>
</table>
### Table 3.1: Single radar selected as “truth” field for producing the “RainSat” probability map

<table>
<thead>
<tr>
<th>Case (dd/mm/yy)</th>
<th>Radar Station</th>
<th>Radar location</th>
</tr>
</thead>
<tbody>
<tr>
<td>01/11/2011</td>
<td>Auckland</td>
<td>(-38.86, 174.77)</td>
</tr>
<tr>
<td>09/11/2011</td>
<td>Christchurch</td>
<td>(-43.53, 172.65)</td>
</tr>
<tr>
<td>20/11/2011</td>
<td>Christchurch</td>
<td>(-43.53, 172.65)</td>
</tr>
<tr>
<td>21/11/2011</td>
<td>Christchurch</td>
<td>(-43.53, 172.65)</td>
</tr>
<tr>
<td>04/12/2011</td>
<td>Wellington</td>
<td>(-41.27, 174.78)</td>
</tr>
<tr>
<td>15/12/2011</td>
<td>Bay of Plenty</td>
<td>(-37.68, 176.17)</td>
</tr>
<tr>
<td>29/12/2011</td>
<td>Napier</td>
<td>(-39.49, 176.88)</td>
</tr>
<tr>
<td>30/12/2011</td>
<td>Wellington</td>
<td>(-41.27, 174.78)</td>
</tr>
<tr>
<td>31/12/2011</td>
<td>Napier</td>
<td>(-39.49, 176.88)</td>
</tr>
<tr>
<td>07/01/2012</td>
<td>Bay of Plenty</td>
<td>(-37.68, 176.17)</td>
</tr>
<tr>
<td>08/01/2012</td>
<td>Wellington</td>
<td>(-41.27, 174.78)</td>
</tr>
<tr>
<td>12/01/2012</td>
<td>Auckland</td>
<td>(-38.86, 174.77)</td>
</tr>
<tr>
<td>13/01/2012</td>
<td>Christchurch</td>
<td>(-43.53, 172.65)</td>
</tr>
</tbody>
</table>

### Table 7.1: Different data assimilation methods and target observations, and the corresponding names of experiments

<table>
<thead>
<tr>
<th>Obs for DA Exp.name</th>
<th>Radar reflectivity</th>
<th>“RainSat”</th>
<th>Precipitating clouds</th>
</tr>
</thead>
<tbody>
<tr>
<td>RK-radar</td>
<td>RK-nudging</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>WVC-radar</td>
<td>WVC</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>RK-RadSat</td>
<td>RK-nudging</td>
<td>RK-nudging</td>
<td>-</td>
</tr>
<tr>
<td>WVC-RadSat</td>
<td>WVC</td>
<td>WVC</td>
<td>-</td>
</tr>
<tr>
<td>RK-RadCld</td>
<td>RK-nudging</td>
<td>-</td>
<td>WVC</td>
</tr>
<tr>
<td>WVC-RadCld</td>
<td>WVC</td>
<td>-</td>
<td>WVC</td>
</tr>
</tbody>
</table>
List of Figures:

Figure 1.1: New Zealand mean annual rainfall (mm) averaged from 1971 to 2000 (Mackintosh, 2001).
Figure 1.2: Wellington C-band radar operated by NZ MetService (photo obtained from Shucksmith (2013)).
Figure 1.3: A simulated cell (left) and the corresponding observation (right).

Figure 2.1: Location of New Zealand and the surrounding nations. Geography dataset is provided by GSHHG (Global Self-consistent, Hierarchical, High-resolution Geography Dataset).
Figure 2.2: The analysis of surface pressure obtained at 1300 NZT 04 November 2013 and 0700 NZT 05 November 2013. Weather charts were provided by New Zealand MetService Ltd.
Figure 2.3: The procedure of deriving rainfall probability with the “RainSat” technique has been adapted from Bellon et al. (1980). $V_{nr}$ and $V_r$ indicate the visible radiances corresponding to the areas without and with radar observed reflectivity, respectively. $IR_{nr}$ and $IR_r$ are similar to $V_{nr}$ and $V_r$ but indicate the infrared radiances. $R_{nr}$ and $R_r$ represent the radar reflectivity corresponding to rain/non-rain areas. $P_{es}$ indicates the probability of rain matrix as a function of VIS and IR.
Figure 2.4: The illustration of the “RainSat” based extrapolation scheme. In the thesis, the extrapolated visible and infrared imageries (represented by VIS’ and IR’, respectively) are coupled with the radar based nowcast (RADAR’) to produce the “RainSat” based nowcasts for subsequent hours.
Figure 2.5: Top-left: VIS imagery; top-right: IR imagery; bottom-right: the “RainSat” derived probability map (The range of optimal probability threshold is between 60% and 100%); bottom-left: corresponding radar observed reflectivity (unit: dBZ), Data were obtained at 0000 UTC 30 December 2011.
Figure 2.6: S scores calculated by Equation 2.2 for different selected probabilities. Here both $a$ and $b$ are set equally to 0.5. The radar threshold for calculating the scores were set to 15 dBZ.
Figure 2.7: Combined CSI and FAR skill scores for the “RainSat” based nowcasts. The verifications were carried out within the range of New Zealand National Radar Network. Due to the decreased size of bivariate frequency distributions table, FAR also decreased with the lead time increased. Unskilled skill scores were calculated based on the combined skill scores for radar based nowcasting at 6 hours (The unskilled reference CSI and FAR are 0.02408 and 0.81301, respectively).
Figure 2.8: Combined CSI and FAR Skill scores for the radar based nowcasts.
Figure 2.9: Right-bottom: observed radar reflectivity at 0000 UTC 01 November 2013 (T+1); Left-bottom: 1 h nowcasting (T+1) from radar echoes extrapolation; Top: 1 h nowcasting (T+1) from the “RainSat” extrapolated probability.
Figure 3.1: CSI (top) and FAR (bottom) scores for the “RainSat” retrieved rainfall probability in terms of the distance between verification area and the selected radar (unskilled CSI: 0.02408; unskilled FAR: 0.81301).
Figure 3.2: CSI (top) and FAR (bottom) scores for the extrapolated “RainSat” probability map (1h: left; 2h: middle; 3h: right column) in terms of the distance between verification area and the selected single radar station (unskilled CSI: 0.02408; unskilled FAR: 0.81301).
Figure 3.3: Probability distributions (> 0%) as a function of VIS (indicated by horizontal axis) and IR (indicated by vertical axis) radiances obtained from GOES satellite for the case at 0000 UTC 30 December 2011. The resolution of satellite data was spatial averaged to $10 \times 10$ km (top) and $50 \times 50$ km (bottom).
Figure 3.4a: Skill scores as a function of spatial resolution of satellite data. The “RainSat” retrieved rainfall maps were obtained using all radars of New Zealand National Radar Network, and verification was carried out within the radar range. Horizontal and vertical axes indicate the spatial resolutions and the associated scores, respectively.
Figure 3.4b: Same as Figure 3.4a but with single radar as the “ground truth”.

165
Figure 3.5: NRMSE in terms of intensity (top) and probability (bottom). All radars of National Radar Network were used to be the “ground truth”. Horizontal and vertical axes indicate the selected resolutions (km) and NRMSE scores, respectively.
Figure 3.6: Skill scores as a function of spatial resolution of satellite data. Vertical and horizontal axes indicate resolutions and the associated scores: correlation coefficient (left-top), Frequency Bias index (right-top), RMSE – intensity (left-bottom) and RMSE – probability (right-bottom).
Figure 3.7: Average spatial - temporal NRMSE contours for the “RainSat” based nowcasting. Horizontal and vertical axes indicate different resolutions and lead times (min), respectively.

Figure 3.8: Normalized standard deviation (NSTD) of different skill scores (vertical axis) as a function of forecast lead time (horizontal axis).
Figure 3.9: The comparisons between the temperatures (0000 UTC 04 December 2011) obtained from WRF, radio sounding and satellite (Cloud Top Temperature). The data was obtained at (174.62, -36.79), where is the location of Auckland Aero Station.
Figure 3.10: Radar retrieved echo top height (ETH) and satellite retrieved cloud top height (CTH) obtained at 0000 UTC 01 November 2011, 0000 UTC 31 December 2011, 0000 UTC 07 January 2012. Radar stations selected to retrieve the ETH are AKL, NPL, BOP and AKL, respectively. The satellite retrieved height for the dBZ free area was set to zero.
Figure 3.11: The average distributions of the height difference calculated over all selected cases.

Figure 3.12: The distributions of the height difference in terms of the different distances from radar station ranging from 50 km to 200 km.
Figure 3.13: Average WRF height difference (m) calculated between two adjunct layers at 0000 UTC 21 November 2011.

Figure 3.14: The Correlation Coefficients (CC) calculated for each selected case at the threshold of 0.02 mm h$^{-1}$. 
Figure 3.15: The scores of RMSE, MAE and FBi calculated for each selected case at the threshold of 0.02 mm h\(^{-1}\).
Figure 3.16: The scores of RMSE, MAE and FBI calculated for each selected case at the threshold of 0.5 mm h$^{-1}$.
Figure 3.17: The scores of RMSE, MAE and FBI calculated for each selected case at the threshold of 2.0 mm h$^{-1}$. 
Figure 4.1: Errors resulted by using the incomplete echoes obtained by radar for extrapolation based precipitation nowcasting

Figure 4.2: Errors resulted by the incomplete echoes obtained by radar for extrapolation based precipitation nowcasting
Figure 4.3: The scheme for combining radar and satellite data for nowcasting.

“Sat_cell1”, “Sat_cell2” and “Sat_cell3” represent three individual cells recognized from the “RainSat” analysis. “Rad_cell1” and “Rad_cell2” are two cells recognized from radar. “Sat_cell1” and “Sat_cell2” are the proportions of cells in the radar range corresponding to “Sat_cell1” and “Sat_cell2”, respectively.
Figure 4.4: Radar, the “RainSat” analysis and the combined analysis obtained at 2300 UTC 31 October 2011 and 0000 UTC 01 November 2011. Extrapolation based nowcasts were generated based on the analysis at these images.

Figure 4.5: Motion vectors retrieved from radar images and the combined analysis for Case 1. In order to show the vectors clear, the resolution of the retrieved motion vectors was smoothed to 15 km.
Figure 4.6: Case1: The comparisons of radar alone extrapolation (left) and the “radar+Rainsat” based extrapolation (middle) with the associated observations (right) from lead times from 1 h to 3 h.
Figure 4.7: The absolute mean bias of dBZ weighted echo centres between observed and extrapolated precipitation in terms of the threshold of 15 dBZ for Case 1.

Figure 4.8: The absolute mean bias of echo area between observed and extrapolated precipitation in terms of the threshold of 15 dBZ for Case 1.
Figure 4.9: Probability of Detection (POD), Equitable Threat Score (ETS), False Alarm Ratio (FAR) and Frequency Bias index (FBi) scores for Case 1 over 6 hours.
Figure 4.10: Radar (left), the “RainSat” analysis (middle) and the combined analysis (right) obtained at 2300 UTC 06 January 2012 and 0000 UTC 07 January 2012. Extrapolation based nowcasting for Case 2 were generated based on the analysis at these images.

Figure 4.11: Motion vectors retrieved from radar images and the combined analysis for Case 2. In order to show the vectors clear, the resolution of the retrieved motion vectors was smoothed to 15 km.
Figure 4.12: The comparisons of radar alone extrapolation and the “radar+Rainsat” based extrapolation with the associated observations from the lead time of 1 h to 3 h for Case 2.
Figure 4.13: The mean absolute bias of dBZ weighted echo centres between observed and extrapolated precipitation in terms of the threshold of 15 dBZ for Case 2.

Figure 4.14: The mean absolute bias of echo area between observed and extrapolated precipitation in terms of the threshold of 15 dBZ for Case 2.
Figure 4.15: Probability of Detection (POD), Equitable Threat Score (ETS), False Alarm Ratio (FAR) and Frequency Bias Index (FBI) scores for Case 2 over 6 hours.
Figure 5.1: Experimental designs for all selected cases. CTL run: initialized with previous 3 h free forecasts; DA run: initialized with radar reflectivity and previous 3 h forecasts.

Figure 5.2: Phase changes of radar observed reflectivity (dBZ) at 0300 (T+0), 0315 (T+15min) and 0330 (T+30min) UTC 01 November 2011.
Figure 5.3: Model outer domain (D01) and inner domain (D02) adopted in this study. The spatial resolutions for D01 and D02 are 9 km and 3km, respectively.
Figure 5.4: Combined ETS scores in terms of different thresholds and lead hours. Horizontal axis indicates forecast lead hours and vertical axis indicates the average scores. Verification thresholds: 0.5 mm h$^{-1}$ (top-left), 1.0 mm h$^{-1}$ (top-right), 2.0 mm h$^{-1}$ (bottom-left) and 5.0 mm h$^{-1}$ (bottom-right).
Figure 5.5: Same as Figure 5.4 but with FAR scores.
Figure 5.6: Same as Figure 5.4 but with FSS scores in terms of different thresholds and scales (Dash line: DA; Solid line: CTL).
Figure 5.7: MSLP analysis (Manual) obtained from Bureau of Meteorology, Australia (top) and the associated WRF simulated MSLP analysis (bottom) at 0000 UTC 01 November 2011.
Figure 5.8: Hourly accumulated precipitation (mm) for the case of 01 November 2011 at 0400 UTC (first row), 0500 UTC (second row), 0600 UTC (third row). CTL runs (left column), DA runs (middle column) and the associated radar observations (right column) are plotted with the threshold of 0.05 mm h⁻¹. A-B indicates the position of the vertical cross section shown in Figure 5.9.
Figure 5.9: Vertical cross section (the position of the vertical cross-section is shown in Figure 5.8) of simulated rain water (kg kg$^{-1}$) (shaded) and vertical winds (m s$^{-1}$) (in black solid contour) at 0400 UTC 01 November 2011 for the CTL run (top) and the DA run (bottom).

Black dot contour indicates the height (m) at each model level.
Figure 5.10: The distributions of maximum rain water (g kg$^{-1}$) for the CTL run (horizontal axis) and DA run (vertical axis) at (T+1), which was 30 minutes after the end of the obs-nudging time window. Left: it shows the situation where assimilated radar derived rain water was larger than the model backgrounds at (T+0). Right: shows the opposite situation where the assimilated derived rain water was smaller than the model backgrounds at (T+0). The relative frequency of “Obs > Model” vs “Obs < model” for this case is 1.76.
Figure 5.11: The comparisons between $\Delta q_v$ and the corresponding $\Delta q_r$ at 0300 UTC 01 November 2011 ($\Delta q_v$ and $\Delta q_r$ were calculated by the reverse Kessler scheme but have not been assimilated into the model by nudging approach). Top: $\Delta q_r > 0$. Bottom: $\Delta q_r < 0$. 


Figure 5.12: The simulated maximum rain water in a column for the DA run (bottom-left) and the CTL run (bottom-right) and the associated radar derived rain water (top) at 0400 UTC 01 November 2011 (threshold: \(0.2 \times 10^{-3}\) kg kg\(^{-1}\)).
Figure 6.1: Land stations used for the verifications for surface temperature and wind.
Figure 6.2: Averaged OMF (observation - forecast) of temperature at (T+1h, 30 minutes after the DA window) over all selected cases for different microphysics schemes in the model. The window for RK-nudging was set to 30 minutes from T+0h to T+30min. (Since there are no observations at T+30mins, 30 minutes lag were given for the verifications).
Figure 6.3: Averaged OMF (observation - forecast) of temperature at (T+1h, 30 minutes after the DA window) over all stations. X-axis indicates the case number and y-axis shows the bias.
Figure 6.4: Same to Figure 6.2 but with U winds.
Figure 6.5: Same to Figure 6.2 but with V winds.
Figure 6.6: POD, ETS and FAR at (T+1h, 30 minutes after the DA window) at different thresholds for different cases. X and y axises indicate the case number and the forecast skills, respectively. Thresholds were ranged between 0.05 $mm$ h$^{-1}$ and 2.0 $mm$ h$^{-1}$.
Figure 7.1: Retrieved precipitation areas using IR alone technique (left), the “RainSat” technique and the associated radar data for 0000 UTC 01 November 2011 (top) and 0000 UTC 31 December 2011 (bottom). Here, the IR alone technique is adopted based on the approach described by Kidder et al., (2005).
Figure 7.2: the vertical distribution of $w(z_h)$ function adopted by Sokol (2010). This distribution was applied in all the WVC related experiments in this chapter.

Figure 7.3: Vertical cross sections of cloud water (shaded), rain water (black line) and water vapour mixing ratio (grey line) for Case 1 (top) and 2 (bottom). The units for all the three selected fields are $\text{kg kg}^{-1}$.
Figure 7.4: Vertical cross sections (at 35.5°S) of cloud water (shaded), rain water (black line) and water vapour mixing ratio (grey line) obtained at 01 UTC of Case 1 (30 min after the data assimilation window). The units for all the three selected fields are \( \text{kg kg}^{-1} \).
Figure 7.5: Vertical slice of (Control – WVC-radar) in terms of cloud water and rain water for Case 1 (top) and Case 2 (bottom).
Figure 7.6: Precipitation forecasts on 01 November 2011 with the threshold of 0.02 mm h⁻¹. From left to right: radar observations, CTL, RK-Radar, RK-RadSat, RK-RadCld and WVC-radar+RainSat. CTL indicates the simulations without the initialization by high resolution data.
Figure 7.7: Same to Figure 7.4 but for Case 2, and at the latitude of 35°S.
Figure 7.8: Precipitation forecasts on 31 December 2011 with the threshold of 0.02 $mm \ h^{-1}$. From left to right: radar observations, CTL, RK-Radar, RK-RadSat, RK-RadCld and WVC-radar+RainSat. CTL indicates the simulations without the initialization with high resolution data.
Figure 7.9.: Combined POD, ETS and FAR scores for all selected cases in terms of different thresholds. All scores were calculated at the spatial scale of 3.0 km over the whole New Zealand. “Solid line”: Control experiment; “+”: RK-Radar; “o”: RK-RadSat; “*”: RK-RadCld; “x”: WVC-radar; “□”: WVC-RadCld; “◊”: WVC-RadSat. X and y axes indicate the lead time and skill scores, respectively.
Figure 7.10: Average Fractional Skill Scores (FSS) in terms of different thresholds and spatial scales. “Solid line”: Control experiment; “+”: RK-Radar; “○”: RK-RadSat; “∗”: RK-RadCld; “×”: WVC-radar; “□”: WVC-RadCld; “◊”: WVC-RadSat.
Figure 7.11: Combined POD scores in terms of different thresholds over the Tasman Sea for a total of 13 cases.
Figure 7.12: Combined ETS scores in terms of different thresholds over the Tasman Sea for a total of 13 cases.
Figure 7.13: Combined FAR scores in terms of different thresholds over the Tasman Sea for a total of 13 cases.
Figure 8.1: Concept of the skills of different forecast schemes. Solid line and dashed line indicate the skill of NWP initialized without and with high resolution radar observations, respectively. Dash-dot line indicates the skill of nowcasting and dot line indicates the skill of NWP initialized with both observation and nowcasting data at T+0 and T+1, respectively.

Figure 8.2: Experimental design: 1) “Radar”: only observed radar reflectivity was assimilated; (2) “Radar+RainSat”: both the observed radar reflectivity and the “RainSat” analysis were
assimilated; (3) “Ext-Radar”: both the observed and extrapolated radar reflectivity were assimilated; (4) “Ext-Radar+RainSat”: the assimilation of the observed and extrapolated radar reflectivity and the “RainSat” analysis.

Figure 8.3: Mean Sea Level Pressure (MSLP) manual analysis for Australian Region at 18 UTC 06 January 2012 (obtained from Bureau of Meteorology, Australia).
Figure 8.4: Radar observations and the associated simulations with different assimilation configurations for 0200 - 0400 UTC 07 January 2011.
Observation and nowcasting data were assimilated at 00 and 01 UTC, respectively.
Figure 8.5: Three hours (0200 – 0400 UTC 07 January 2012) simulated precipitation accumulations for different data assimilation schemes and the associated observations (top-left).
Figure 8.6: Combined forecast skill scores (POD, ETS and FAR) for the event of 07 January 2012. “Solid line”: “Control”; “+”: “Radar”; “•”: “Ext-Radar”; “∗”: “Radar+RainSat”; “X”: “Ext-Radar+RainSat”.
Figure 8.7: Combined skill scores (POD, ETS and FAR) in terms of different thresholds. “Solid line”: “Control”; “+”: “Radar”; “o”: “Radar+RainSat”; “*”: “Radar”; “Δ”: “Ext-Radar+RainSat”. (The verifications were begun at the lead time 1 hour).
Figure 8.8: Average correlation coefficients for different forecast schemes (The verifications were begun at the lead time of 1 h).
Figure 8.9: Combined Fractional Skill Scores (FSS) for different forecast schemes in terms of different thresholds. “Red”: “Control”; “Green”: “Radar”; “Blue”: “Ext-Radar”; “Cyan”: “Radar+RainSat”; “Magenta”: “Ext-Radar+RainSat”; “Black”: “Nowcasting”; X and y axes indicate lead time and the skill scores, respectively.