Time-Lagged Cloud-Resolving Ensemble Quantitative Precipitation Forecasts for An Extreme Rainfall Event in Central Vietnam

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Abstract

An extreme rainfall event occurred from 8 to 11 December 2018 along the coast of central Vietnam. The maximum rainfall amount in 72 hours observed was over 900 mm, and the associated heavy losses made it both a record-breaking and significant event (hereafter, abbreviated as the D18 event). The analysis on the D18 event shows that the interaction of the low-level cold surge, originating in China, with the low-level easterlies wind over the South China Sea (SCS) led to the formation of a strong low-level convergence and then local deep convections. Some preexisting convection was also advected onshore by the easterly flow into central Vietnam against the Annamite Range. Besides, the strong easterly and strong southeasterly anomaly winds also played an important role in transporting moisture from the tropics across the SCS toward central Vietnam. These conditions led to the extreme rainfall along the eastern central coast due to the Annamite Range's barrier effect.

Evaluation of the predictability of the D18 event by the high-resolution time-tagged ensemble predictions using the Cloud-Resolving Storm Simulator (CReSS) indicated that CReSS well-predicted the daily as well as 72-h accumulated rainfall during the D18 event at the lead times of day 1, day 2, and day 3. However, the predictive skill is reduced at the extended lead time beyond 3 days. These can be related to the rapid changes in atmospheric disturbances with time during the event due to the special position of Vietnam in the tropics.

This is the first time a cloud-resolution model (CRM) is applied to forecast extreme rainfall in Vietnam, and the results are encouraging. Therefore, our result will provide the motivation to carry out further research on the predictability of the extreme rainfall in Vietnam by using the CReSS model.

1. Introduction

Heavy to extreme rainfall causes natural disasters, such as deaths, flooding, inundation, landslides, and erosion. Viet Nam is one of the most disaster-prone countries in the world with many different types of natural hazards. In Vietnam, Central Vietnam is most affected by natural disasters and climate change. Storms and extreme rainfalls are the most frequent affecting this area (Chen et al., 2012a). For example, the D18 event, its peak 72-h accumulated rainfall over 900 mm, and resulted in 13 deaths, an estimated 1200 houses inundated, around 12,000 hectares of crops destroyed, and some 160,000 livestock killed (Tuoi Tre newspaper). Furthermore, according to climate change and sea-level rise scenarios for Vietnam, extreme precipitation events will increase in both their frequency and intensity in the future (Monre 2016). Hence, how to improve the ability in QPF of heavy rainfall events is very important. However, among all meteorological variables, precipitation is considered the most complex and difficult to predict. So, in order to improve the ability of QPF of heavy rainfall events, we need not only better to understand the mechanisms leading to heavy rainfall but also develop forecasting tools, particularly in the area of numerical weather prediction (NWP). At the facet of mechanism research that can lead to heavy or extreme rainfall, studies in the past have been shown main factors that led to heavy rainfall events in this region, such as the combined effect of cold surges, tropical easterly disturbances, and topography (Chen et al. 2012a; Nguyen-Le and Matsumoto 2016; van der Linden et al. 2016a). Similar results were also found in Yokoi and Matsumoto (2008) when they investigated synoptic-scale atmospheric conditions over the SCS that caused heavy rainfall in central Vietnam on 2-3 November 1999. These authors confirmed that the coexistence of the cold surge and tropical depression–type disturbance is an important factor for the occurrence of heavy precipitation in central Vietnam. There was the cold surge without a tropical depression–type disturbance, would not lead to much precipitation. Besides, according to Nguyen-Thi et al. (2012), rainfall in central Vietnam is strongly affected by tropical cyclones that originate from the northwest Pacific. Some studies have examined the link between rainfall and El Niño/La Niña-Southern Oscillation (ENSO) for Vietnam and concluded that central Vietnam has more (less) rainfall during the La Niña (El Niño) years (Yen et al. 2010; Thang Van Vu et al. 2015). For D18 event, our analysis based on datasets such as reanalysis, satellite data, radar data indicates several main factors responsible for the D18 event: The strong northeasterly winds, originating in China interacts with the strong low-level easterly winds over the SCS, And then blow into central Vietnam and was blocked by Truong Son Range, led to the formation of a strong low-level convergence and then local deep convections. Besides, some preexisting convection was also advected onshore by the easterly flow into central Vietnam against the Annamite Range. These analyses also point out that the easterly wind also plays an important role in transport moisture bands across the South China sea that originated from the Pacific Ocean and the southern part of the SCS into central Vietnam. At the facet of NWP, nowadays, with the rapid advance in computer technology increasing computer power, and the advantages of ensemble forecast, a range of possible outcomes can be generated by the NWP in days ahead, or longer into the future. The ensemble forecast is more and more commonly applied in operational weather prediction offices to improve the quality of weather prediction. Studies on the world have demonstrated the feasibility and good quality of ensemble prediction at longer ranges. For example, some studies have shown high skill in quantitative precipitation forecasts (QPF_s) for extreme rainfall produced by typhoons in Taiwan using the CRM with high-resolution and time-lagged approach (e.g., Wang et al. 2016; Wang 2015; Wang et al. 2014; Wang et al. 2013).

By advantages of time-lagged ensemble QPFs for both typhoons and heavy rainfall events approach has been proved. In this paper, we focus on presents the high-resolution ensemble prediction with a time-lagged approach and evaluates predictability of the D18 event in the high-resolution time-lagged ensemble prediction system using the CReSS Model. The rest of this study is organized as follows: Section 2 describes the datasets and methodology used in the study. Results are presented in section 3. Finally, conclusions are given in section 4.

2. Data and method

2.1. Data

In order to perform this study, some data sources have been used: (1) the National Centers for Environmental Prediction (NCEP) operational Global Forecast System analysis and forecast grids with 0.25 x 0.25 degrees global latitude-longitude grid are used as initial and boundary conditions for CReSS predictions. (2) The reanalysis data provided by the European Centre for Medium-Range Weather Forecasts (ECMWF) interim reanalysis data (ERA-Interim) is used to delineate the subsynoptic weather patterns during the D18. Its resolution is 0.25º x 0.25º in longitude and latitude, and its temporal interval is 6h (Dee et al. 2011). (3) Observed rainfall data at 69 automated rain gauge stations across mid-central Vietnam with daily resolution (1200–1200 UTC, i.e., 1900–1900 LT) between Dec 8 – Dec 13, 2018, were used to assess the model results. (4) The Tropical Rainfall Measurement Mission (TRMM) multi-satellite precipitation analysis 3B42 Version 7 data used to analyze the D18 and assess the model results (Huffman et al. 2013).

2.2. Model and experiment setup

This study used the Cloud Resolving Storm Simulator (CReSS) model version 3.4.2, which was developed by Kazuhisa Tsuboki at the Hydrospheric Atmospheric Research Center (HyARC) of the University of Nagoya, and by Atsushi Sakakibara at Research Organization for Information Science and Technology. For more detailed information, readers can refer to "Numerical Prediction of High-Impact Weather Systems" document (Tsuboki, and Sakakibara, 2007).

This study made a total of 21 members, with the first members run at 12 UTC 3 December 2018, and the last member-run at 12 UTC 8 December 2018. Between the first and the last members is multiple members that running every 6-h. The basic information of experiments that performed in this study, including domain setup with illustrating image and basic configuration shown in Table 2.2.

2.3. Verification of model results

In order to verify QPFs, this study used some popular methods for verification of rainfall, such as (1) Verify by visual comparison between the model results and the observation data. Daily accumulate rainfall at 69 automated rain gauges over study area was collected and compute to visually compared with the model results. (2) Verify by using Statistical methods to evaluate the skills of the model at different rainfall thresholds with the lowest rainfall threshold in evaluation is 0.05 mm and extends to 900 mm for three days. These scores are listed in table 2.3 along with their formulas, the perfect scores, and the worst scores, respectively. To applies these scores for verifying the model results. First, the rainfall from model results, and the observation data, a table of contingency will be made. In which, if both the model and the observation results show rain, the prediction is considered Hit (H). If the model does not show rain, but the observation shows rain, the prediction is considered Miss (M). If the model shows rain while the observation is not, the prediction is considered False alarm (F). Finally, if both the model and the observation results do not show rain, the simulation is

Table 2.2: The basic information of experiments

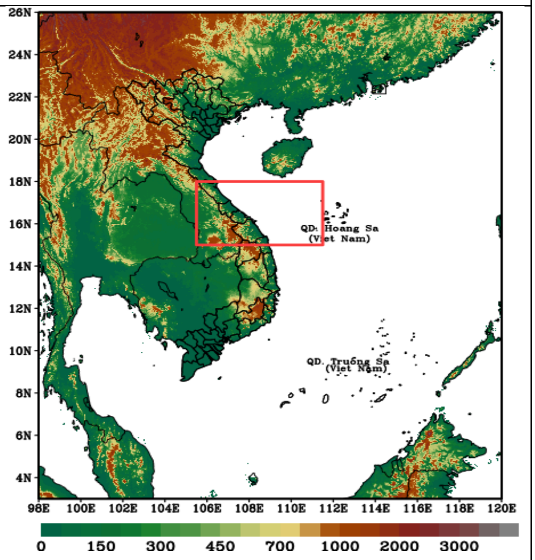
Domain setup and basic configuration		Domain and topography (m)
Domain size	3N – 26N; 98E – 120E	
Grid dimensions (x,y,z)	912 x 900 x 60	
Grid spacing	2.5 km x 2.5 km x 0.5 km	
Projection	Mercator	
Frequency of forecast	Four-time per day (00, 06, 12, 18 UTC)	
Forecast range	Eight days (192 hours)	
Topography and SST	Real at $(1/120)^o$ and NCEP analyses on a 0.25^o x 0.25^o grid	
Cloud microphysics	Bulk cold-rain scheme (six species)	
Ensemble size	21 members	A thick red box marks the study area

Table 2.3. List of statistic scores

Name	Formula	Perfect score	Worst score
Frequency Bias **(FBI)**	**(H+F)/(H+M)**	1	<<1 or >>1
Probability Of Detection **(POD)**	**H/(H+M)**	1	0
False Alarms Ratio (**FAR)**	**F/(H+F)**	0	1
Threat Score **(TS)**	**H/(H+M+F)**	1	0

correct Negative (Daniel S.Wilks 2006). After that, these scores will be calculated by corresponding formulas in table 2.3.

Besides, the Fraction Skill Score (FSS) (Roberts and Lean 2008) also applied to evaluate the model results. FSS's score shows that a forecast with perfect skill has a score of 1; a score of 0 means zero skill.

$$FSS=1-\frac{\frac{1}{N}\sum_{i=1}^{N}(P_f-P_o)^2}{\frac{1}{N}\sum_{i=1}^{N}P_f^2+\frac{1}{N}\sum_{i=1}^{N}P_o^2} \qquad (1)$$

where N is the number of the observation station, p_f is the forecast values, p_o is the observed value.

2.4. The ensemble spread (standard deviation)

The ensemble spread is considered a measure of the difference between the members to the ensemble mean, and known as the standard deviation (Std). In other words, the ensemble spread will reflect the diversity of all possible outcomes. Hence, the ensemble spread is often applied to predict the magnitude of the forecast error. If small spread indicates high theoretical forecast accuracy, and large spread indicates low theoretical forecast accuracy. Spread is computed by formulated below:

$$\text{Spread} = \sqrt{\frac{\sum_{i=1}^{n}(x_i-\mu_x)^2}{n-1}} \qquad (2)$$

where x_i is the prediction value of member i, μ_x is the ensemble mean, N is the number of ensemble members.

3. Results

As we know, an ensemble weather forecast is a set of forecasts that present the range of future weather possibilities obtained from multiple separate members. Hence, the simplest way to use the ensemble forecasts is by computing the ensemble mean. Besides, some studies showed that the ensemble mean will have a smaller error than the individual ensemble members. This error reduction arises because high predictability features that the members agree on are accentuate by the mean, while low-predictability features that the members do not agree on are filtered out or heavily dampened (e.g.; Murphy 1988, Surcel et al. 2014). Therefore, this section will show the ensemble mean of rainfall scenarios and its spread for 72-h rainfall of the D18.

Figure 3.1 shows the scenarios of the ensemble mean of 72-h rainfall and its spread for periods of 12 UTC 08 December to 12 UTC 11 December. With five groups of the ensemble mean evaluated. In which, the ensemble mean of the last 05 members includes members executed within ranges days 0-1 before the target date. The ensemble mean of the last 09 members includes members executed within ranges days 0-2 before the target date. The ensemble mean of the middle 08 members includes members executed within ranges days 2-3 before the target date. The ensemble mean of the first-08 members includes members executed within ranges days 4-5 before the target date. The ensemble mean of the 21 members includes members executed within ranges 0-5 days before the target date. Results show that the ensemble mean of the last 05 members stands out with high-quality QPFs and closer to the observed rainfall data than the rest of the ensemble mean. The spatial distribution of rainfall in this scenario is considered similar to reality. However, the 72-h rainfall amount is lower than in reality.

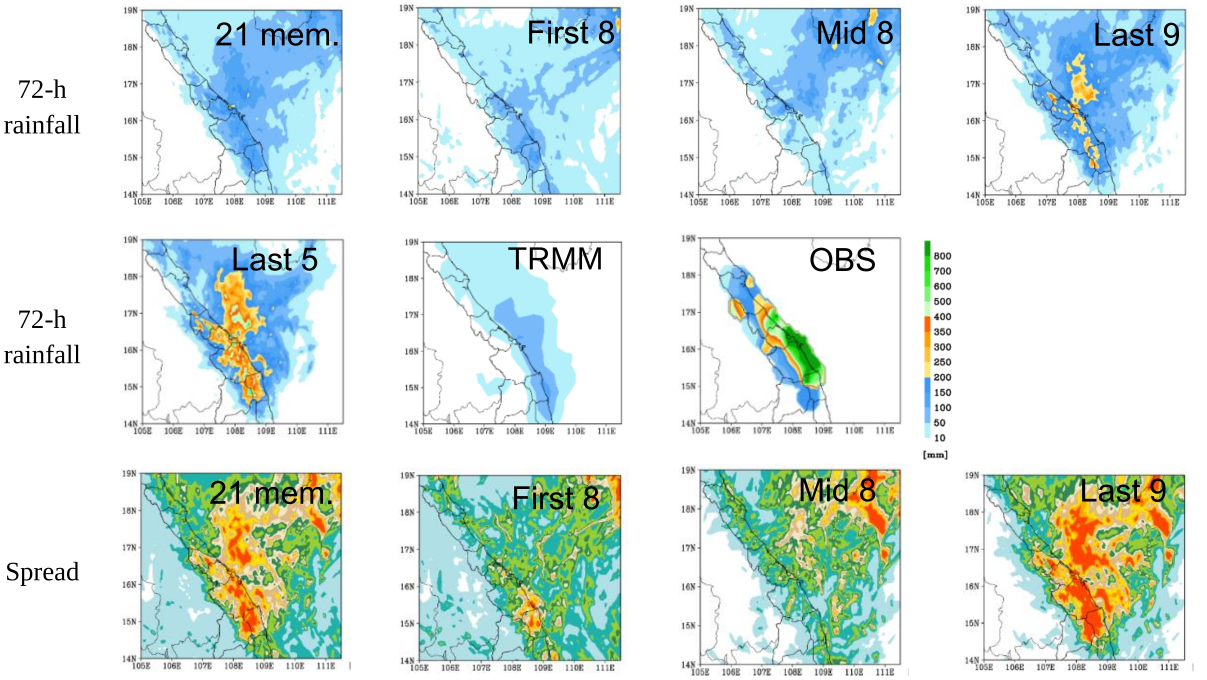
In particular, figure 3.2a shows at 250 mm, the ensemble means of the last five members have TS=0.5 (POD=0.6, FBI=0.9, FAR=0.3, not shown), meanwhile, the ensemble mean of the nine members has TS=0 (POD=0, FBI=0, FAR=1, not shown). The ensemble means of the middle 08 members, the ensemble means of the first eight members, and the ensemble mean of 21 members has no skill scores. At 350 mm, only the ensemble means of the last five members have skill scores with TS=0.2 (POD=0.3, FBI=FAR=0.4, not shown). At 500 mm, skill scores of the ensemble mean of the last five members, such as TS=0 (POD=FBI=0, FAR has no scores, not shown), while the observed rainfall amount recorded greater than 800 mm. Contrariness, the ensemble mean of the mid 08 members is considered worst-quality QPF_s due to the skill scores is the lowest compared to the rest of ensemble means. The FSS score (Fig. 3.2b) also shows that the ensemble mean of the last 05 members has the highest quality QPF with FSS=0.7, and the lowest quality QPF is the middle 08 members (FSS=0.14). Besides, FSS score of the ensemble mean of 21 members is 0.35.

Furthermore, spread scenarios show the ensemble mean of the last five members has the largest spread, this meaning that in scenario of the spread is largest, the rainfall amount predicted by the model is very closer to observed rainfall data. Besides, it is clear to see that the ensemble means of the last 09 members and the ensemble mean of all members has a very larger spread, although the 72-h rainfall scenarios are mostly lower than 200 mm. These wide ranges of the spread may be related to individual members in these groups, which did not predict rainfall well due to the incorrect predicted of the surface wind field (Fig. 3.1).

The maps of the probabilities distribution in Figs. 3.3 indicating that over inland, the probabilities that ensembles can reach the threshold at 100 mm of rain is over 70% of the last 5 members, 40-60% for the last 9 members, 30-40 % for the first 8 members over the haft of the south part of central, 20-40 % for 21 members, and just is 10-20% for the middle 8 members over a haft of the north part of the study area. For thresholds greater than 100mm, there is a 50-60 % chance for the last 5 members, 30-40 % for the last 9 members, and 10-20 % of 21 members reached the threshold at 300 mm of rain. However, only the last 5 and the last 9 members can reach a threshold at 500 mm of rain with probabilities is 20-30%. No one group in 5 groups of the ensemble can touch threshold at 800 mm of rain.

By analysis above show that the model has well predicted 72-h rainfall of D18 event within the lead time of 1 - 2 days before the target date. However, the model has not well predicted 72-h rainfall of the D18 event with lead time 2-3 days before the target date as analyzed and indicated in the previous paragraphs. This problem can relative to quickly change in the real turbulent atmosphere with time (unit is an hour), leading to much difference in the initial data. Meanwhile, all members of this study are executed every 6h. In particular, initial state analyzes based on GFS datasets at 12 UTC 08, 12 UTC 09, and 12 UTC 10 (not shown) indicate that most of the middle 08 members did not predict moisture convergence/divergence over the study area.

Furthermore, ensemble sensitive analysis shows that the 24-h accumulated rainfall of every single day of the D18 event is strongly sensitive to initial conditions, and is strongest sensitive on Dec 10 (not shown). Besides, as we know, the computational errors will arise at every time step of the integration and will build up cumulatively. Hence, the result of the middle 08 members is the worst from each other.



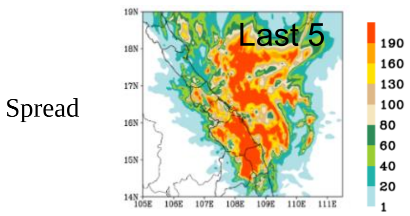


Figure 3.1. Ensemble mean and their spread (shaded, scale at right) from all 21 time-lagged members, executed every 6 h from 1200 UTC 3 Dec to 1200 UTC 8 Dec, for the 72-h period from 1200 UTC 8 Dec to 1200 UTC 11 Dec.

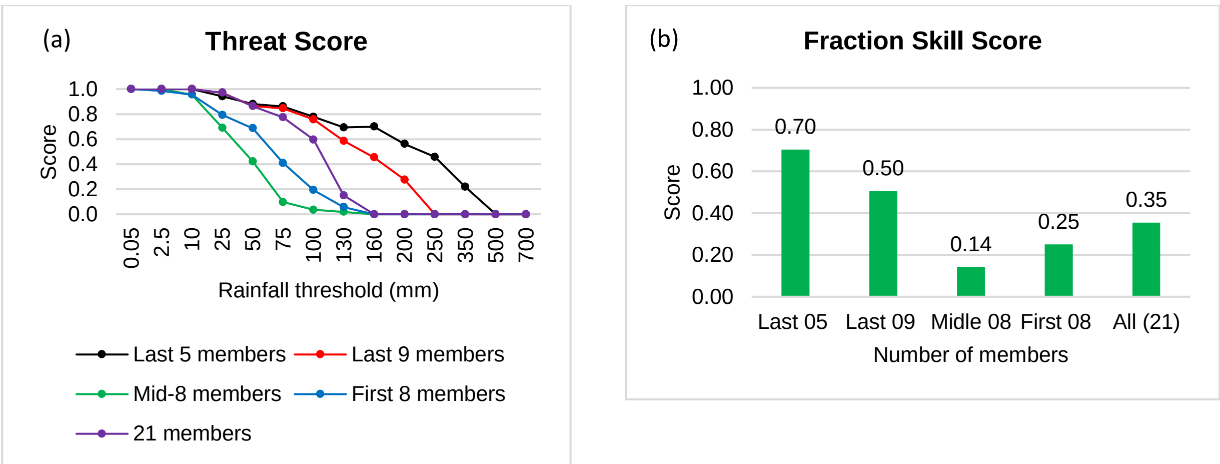


Figure 3.2. Statistic scores for 72-h mean rainfall, obtained from twenty-one 8-day forecasts for the period between 1200 UTC 08 and 1200 UTC 11 December 2018.

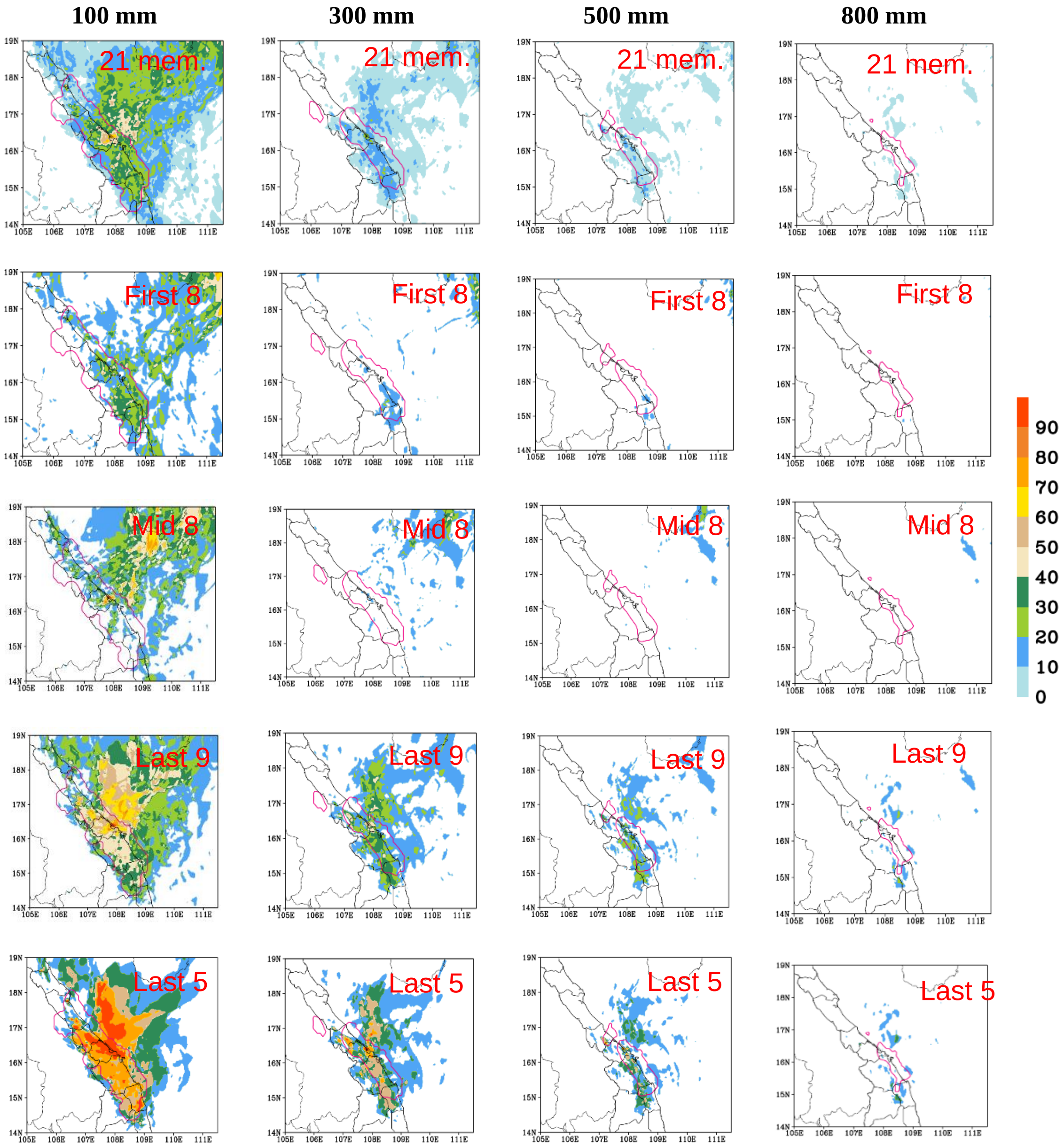


Figure 3.3 Probability distribution (%; shaded, the scale at right) from all 21 time-lagged members, executed every 6-h from 1200 UTC 3 Dec to 1200 UTC 8 Dec, reaching thresholds of 100, 300, 500, and 800 mm, for the 72-h period from 1200 UTC 8 Dec to 1200 UTC 11 Dec. The observed areas at the same thresholds are depicted by the pink contours. For each picture, red labeled at the top-right corner show the number of members grouped to calculate the probability distribution.

4. Conclusion

This study focused on the analysis of an extreme precipitation event that occurred on 08 - 11 December 2018 along the coast of the central of Vietnam and its predictability in the high-resolution time-lagged ensemble prediction system using the CReSS Model. Evaluation of the predictability of the D18 event by the high-resolution time-lagged ensemble prediction system using the CReSS model, indicating that CReSS well-predicted 72-h rainfall fields of the D18 event within the lead-time 0 – 2 days before the target date. In particular, results show CReSS has high skills in heavy-rainfall QPFs for this case with the FSS scores for the 72-h rainfall are 0.7 at the lead time 0-1 day and 0.5 at lead time 0 - 2 days before the target date (Fig. 3.2b) as analyzed previous sections**.** These good results are due to the model having good predicts of other meteorological variables, such as surface wind fields. However, these prediction skills are reducing at extending lead time (longer than 3 days), and it is challenging to achieve the prediction of QPF for rainfall thresholds greater than 100 mm with lead time longer than 3 days.

These can be relevant to rapid changes in atmospheric disturbances with the time due to the special position of Vietnam in the tropics.

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