

A Downscale Experiment on Numerical Weather Prediction in Indochina Region with a Mesoscale Model

Palikone THALONGSENGCHANH^{*,**}, Shigenori OTSUKA^{*} and Shigeo YODEN^{*}

^{*} Department of Geophysics, Graduate School of Science, Kyoto University

^{**} Department of Meteorology and Hydrology, Lao PDR

Synopsis

We perform a downscaling hindcast experiment in Indochina region with a fine-mesh mesoscale regional model under the assumption of the “perfect forecast” produced by a global numerical weather prediction model. The experiment is done for June-to-September of the years 2003-to-2006 in the rainy season. Validations of the downscaling hindcast are made with temperature data obtained at 17 surface stations in Laos. We propose a new method to diagnose the improvement of correlation or bias by the downscaling using a scatter diagram. The correlation between the model results and observations is higher in July and September than that in June or August. We find a rather common bias for all the stations of about 1 K in the model in addition to the bias due to the elevation error of each station.

Keywords: numerical weather prediction, Indochina region, mesoscale model, downscaling

1. Introduction

The climate of Lao PDR in Indochina (e.g., Thalongsechanh and Sokhathammavong, 2002) is tropical with distinct dry and wet seasons corresponding to two major wind regimes similar to that observed in South East Asia, that is, the Northeast Monsoon and the Southwest Monsoon. As Lao is an inland country, it is protected from strong wind and typhoon-induced storm surge. However, active monsoon and tropical depressions during the Southwest Monsoon period bring heavy rainfall very often due to the dynamic cooling and orographic lifting effects on the western side of the mountain range along the Lao-Vietnam border.

Weather conditions during the wet season in Lao have large year to year variations with potential water-related disasters such as flooding and drought. Seasonal forecast schemes in Lao have evolved over periods through trial and error, and the current

forecasts scheme relies on various predictors and their relative influence on the future state. El Nino/Southern Oscillation (ENSO) is one of the major drivers of climate variability in most parts of South East Asia. The prediction of El Nino several months to one year in advance will provide greater opportunity to improve the seasonal predictions. The flood frequency of the Mekong River has been widely discussed under Mekong River Commission Secretariat, and a variety of statistical models to forecast floods have been proposed by using hydrological data.

Operational forecasts from month to season time scales are available in several forecast centers based on global numerical model outputs. However, information with sufficient spatial resolution is needed in the estimation of hydrological afflux, particularly river run-off that may potentially produce severe floods under extreme weather conditions. Thalongsechanh et al. (2006) was the

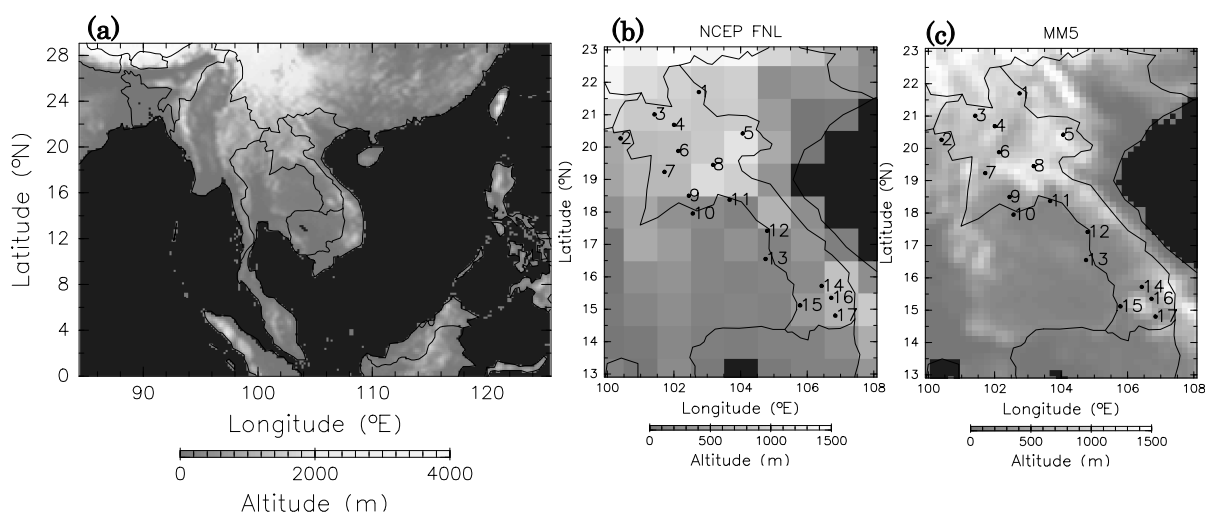


Fig 1. (a) Map of the model domain. Gray tone shows the terrain elevation. (b) Terrain in NCEP FNL with station numbers. (c) Terrain in MM5 with station numbers.

first attempt to apply a mesoscale model for downscale numerical weather predictions (NWP) in Lao PDR to obtain information with high resolutions. The main concern of that work was to validate the model performance through dynamical downscaling of the global model output for weather forecasting in Indochina region.

In this study, we perform downscaling hindcast experiments further for several months in the wet Southwest Monsoon period under the assumption of the “perfect forecast” produced by data assimilation in a global NWP system. The downscaling is made with the fine-mesh mesoscale regional model same as the previous work (Thalongsengchanh et al., 2006).

2. Model description

We use the Fifth-Generation Pennsylvania State University / National Center for Atmospheric Research (NCAR) Mesoscale Model (MM5) version 3.7.4, which is a non-hydrostatic regional model nested to a global dataset. The model domain covers the Indochina region including the South China Sea (85E–125E in longitude and Equator–30N in latitude) on a Mercator projection as shown in Fig. 1a. The domain has 230×170 grids with the grid interval of 20 km. The model has 23 levels from the surface to 100 hPa with nonuniform vertical resolutions. We use a cumulus parameterization scheme “Kain-Fritsch 2” with a

parameterization of shallow convections, and microphysics “Mixed-Phase” with rain, cloud water, ice, and snow. Both longwave and shortwave radiation are calculated, including longwave radiation from clouds.

We used the National Centers for Environmental Prediction (NCEP) Global Final Analyses (FNL) for initial and boundary conditions which are necessary for the entire time integration period. The NCEP FNL data are available for every 6 hours with 1×1 degree horizontal resolution as shown in Fig. 1b.

We perform 5-day forecasts with 1-day overlaps to obtain long term data, discarding initial 1-day of each run. Model output is stored by every 3 hours. The experiment was done for June, July, August, and September in the wet Southwest Monsoon period of the years 2003, 2004, 2005, and 2006.

Evaluation of a downscaling hindcast is made with surface temperature at 17 observation stations in Lao PDR. The observational time interval is 3 hour, though at some stations only daytime data are available. We use daily averaged values in the following analysis. Figure 1 shows the map of Lao PDR and neighboring countries with terrain height and the locations of 17 stations of which data are used in this study. Figure 1b shows the terrain elevation for NCEP FNL in gray scale, while Fig. 1c shows the terrain used in the present MM5 experiments. We can see much better horizontal

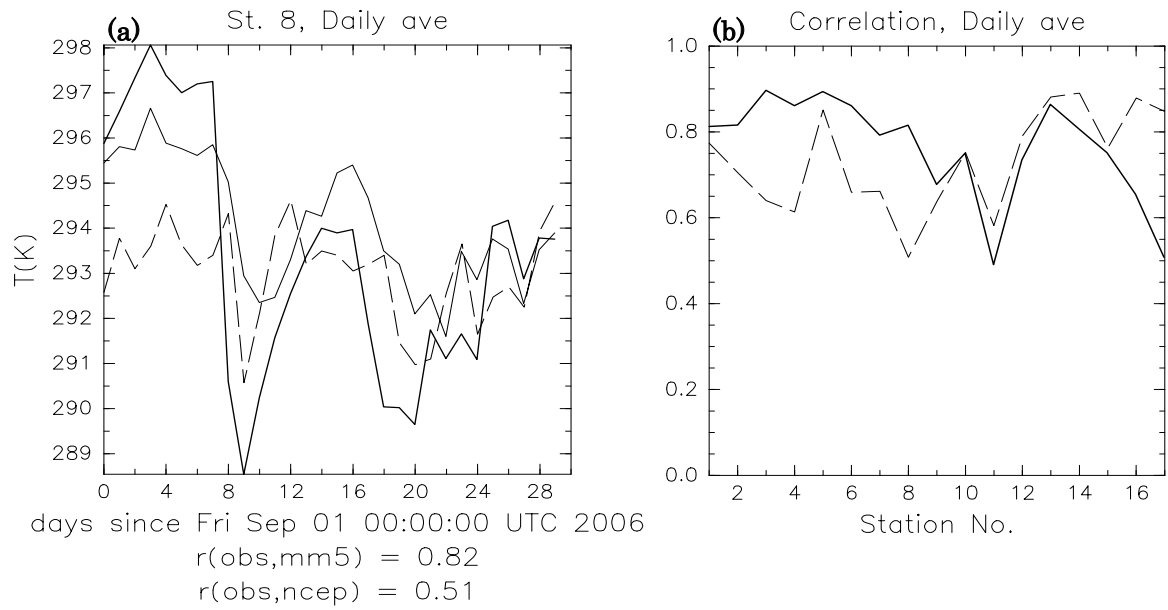


Fig. 2. (a) Time series of daily average surface temperature: MM5 output (thick solid line), the observation (thin solid line), and NCEP FNL (thin dashed line). (b) Correlation values between MM5 and observation (thick solid line), and those between NCEP FNL and observation (thin dashed line).

resolution in MM5; in NCEP FNL we have multiple stations in a cell, while all the stations are well-resolved in MM5. Small-scale mountains and valleys resolved in MM5 will be useful for better forecasts by downscaling.

3. Output example

Figure 2a shows a time series of daily average surface temperature at station no. 8 in September 2006. Three lines show daily average data of observed surface temperature (thin solid line), surface temperature at the nearest grid point in NCEP FNL (thin dashed line), and temperature at 2 m above ground level at the nearest grid point in MM5 (thick solid line). The correlation between observation and MM5 output is 0.82, which is greater than that between observation and NCEP, 0.51. This is the best example of improvement for this month by the downscaling.

Figure 2b shows correlation values at the 17 stations. From station no. 1 to station no. 9, the MM5 output is better than NCEP FNL, while it is not for the other stations. The downscaling technique does not always bring improvement of forecasts, particularly station no. 16 and 17 for this month.

4. Correlation analysis

4.1 Methods for analysis

We use scatter plots of two values of monthly correlations to evaluate results of downscaling numerical experiments; one is correlation between the station observations and the corresponding MM5 results, and the other is correlation between the observations and the NCEP FNL data. The quality of FNL varies in space and time, and the MM5 output is highly affected by the quality of FNL because MM5 is constrained by FNL through the initial and the boundary conditions. If we evaluate both the quality of MM5 results and the quality of FNL simultaneously, we can split the effects of the initial and the boundary conditions and those of the downscaling.

Figure 3 shows examples of the scatter diagrams of correlation values (x , y) for four months, where the horizontal axis x is correlation between the observations and FNL for 17 stations and four years, while the vertical axis y is correlation between the observations and MM5 output. There are three lines in each diagram: $x=0.5$, $y=0.5$, and $x=y$. We divide each panel into five sub-regions with the lines: (1) $x>0.5$, $y>0.5$, and $x<y$, (2) $x>0.5$, $y>0.5$, and $x>y$, (3) $x<0.5$ and $y>0.5$, (4) $x>0.5$ and $y<0.5$, (5) $x<0.5$ and

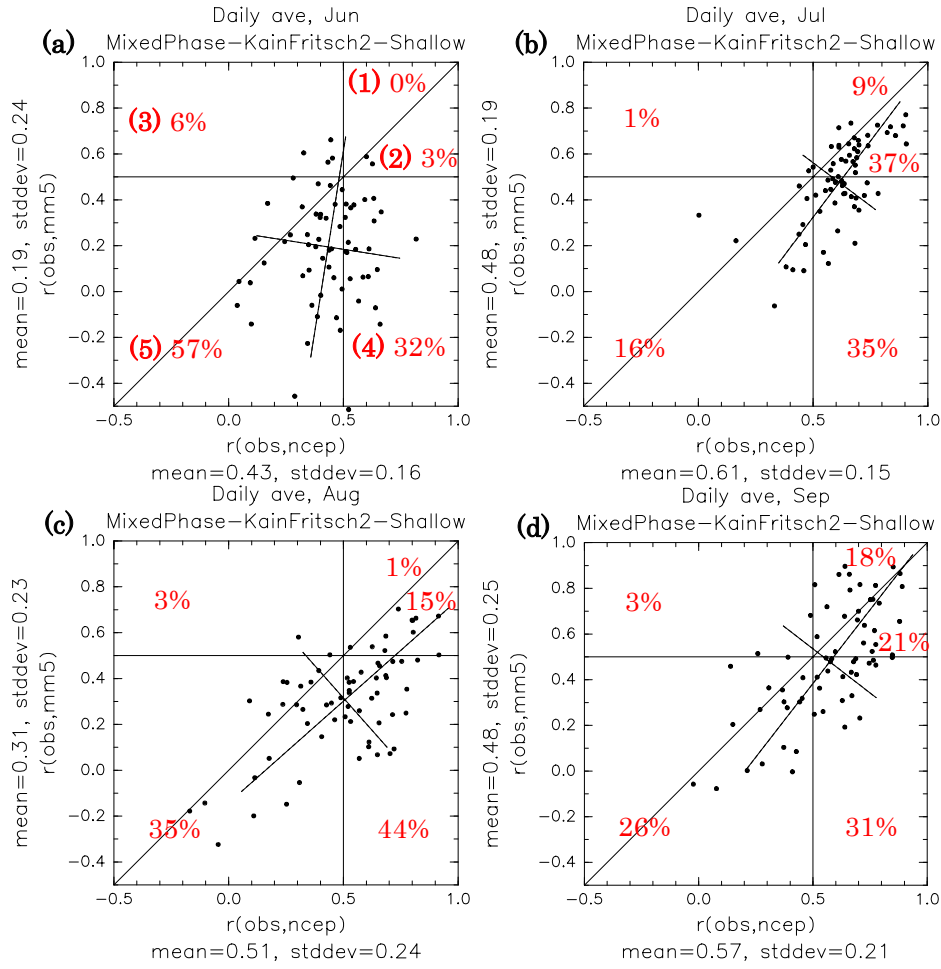


Fig. 3. Scatter diagrams of monthly correlation values of daily average surface temperature of observation, MM5, and NCEP FNL. The x axis shows correlation between observation and FNL, while the y axis shows correlation between observation and MM5. (a) June, (b) July, (c) August, and (d) September.

$y < 0.5$.

The data points in the boxes (1) and (3) mean improvement by the downscaling. In these cases, correlation between the observation and MM5 output is better than that between the observation and FNL. In the case of the box (3), the correlation between the observation and FNL shows lower than 0.5, but the improvement by the downscaling is very high. The data points in the boxes (2) and (4) mean that NCEP is better than MM5. In these cases, the downscaling does not achieve improvement. The data points in the box (5) mean correlation values less than 0.5 for both x and y . In this case, the assumption that FNL is a perfect forecast is no longer guaranteed. The downscaling has little meaning even if $y > x$. Note that correlation between the observations and NCEP FNL is usually better than that between the observations and MM5 results because FNL is a product of contemporary data

assimilation scheme which is constrained by observation data.

4.2 Month-to-month variation

Figure 3 shows the scatter diagrams for June, July, August, and September. Each panel contains 68 points (four years and 17 stations), and the percentages of data points in the boxes (1)-(5) are shown within the boxes. In September, 21% of the points are in the boxes (1) and (3), while 52% of the points are in the boxes (2) and (4). The rate of the improvement in September is the highest in these four months. In July, 10% of the points are in the boxes (1) and (3), while 72% of the points are in the boxes (2) and (4). This shows that the rate of the improvement in July is smaller than that in September because FNL has better performance in July than in September. In August, 4% of the points are in the boxes (1) and (3), while 59% of the points

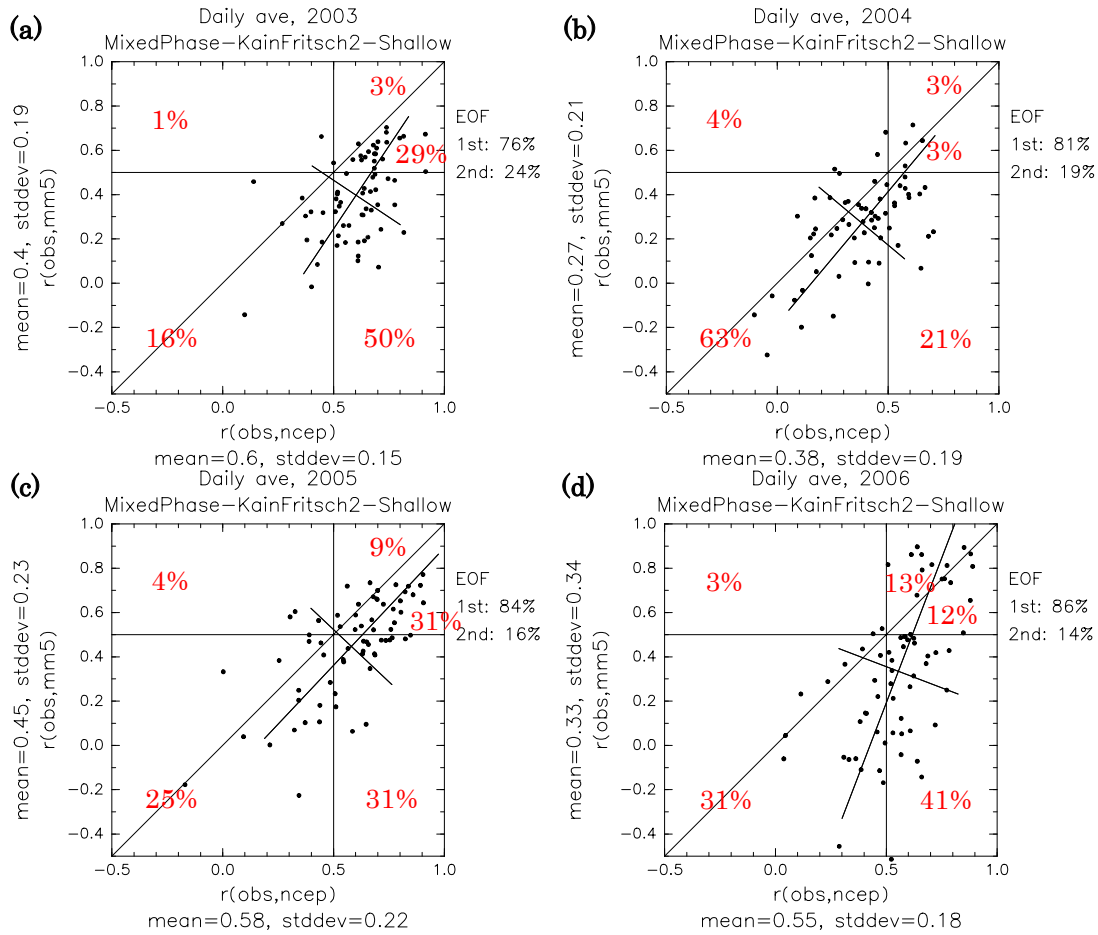


Fig. 4. Same as Fig. 3, but for years (a) 2003, (b) 2004, (c) 2005, and (d) 2006.

are in the boxes (2) and (4). In June, 6% of the points are in the boxes (1) and (3), while 35% of the points are in the boxes (2) and (4). In June, the percentage of the points in the box (5) is 57%, which is the highest in these four months. This means that the performance of FNL is the worst in June, which also makes the performance of the downscaling by MM5 the worst.

The month-to-month variation of the correlation between observed surface temperature and surface temperature in FNL and then in MM5 can be explained by the seasonal march of the summer monsoon in Southeast Asia. In June, pre-monsoon disturbances frequently appear in small sub-grid scales, by which FNL becomes poor. In August, tropical cyclones occur frequently in Indochina region, which are difficult to reproduce in a global objective analysis. Thus, the quality of FNL is lower in June and August than in July and September.

4.3 Year-to-year variation

Figure 4 shows the same diagrams as Fig. 3, but

for each year from 2003 to 2006. In 2003, variance of the points is smaller than that in other years; 50% of the points are in the box (4). The percentage of the points in the boxes (1), (2), and (4) is 82%. This means that the performance of FNL is high in 2003, and the rate of the improvement is not so high; only 4% of the points are in the boxes (1) and (3). In 2004, on the other hand, 63% of the points are in the box (5); this means that both the performance of FNL and the performance of the downscaling by MM5 are the worst in these four years. The percentage of the points in the boxes (1) and (3) is 7%. In 2005, 13% of the points are in the boxes (1) and (3); the rate of the improvement is higher than that in 2003 and 2004. In 2006, 16% of the points are in the boxes (1) and (3), which is the highest value in the four years.

5. Bias analysis

5.1 Station-to-station variation

Figure 5 shows scatter plots of two values of monthly bias of surface temperature at three

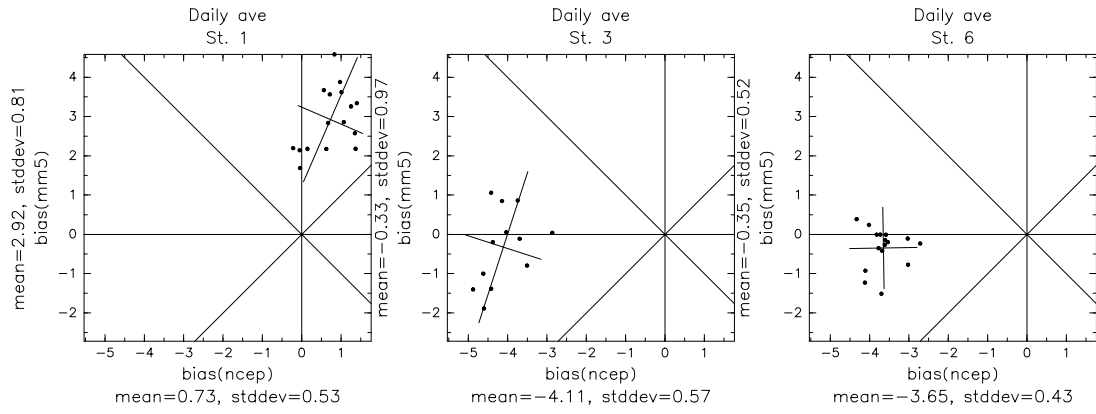


Fig. 5. Bias of the NCEP FNL and MM5 for station no. 1, 3, and 6.

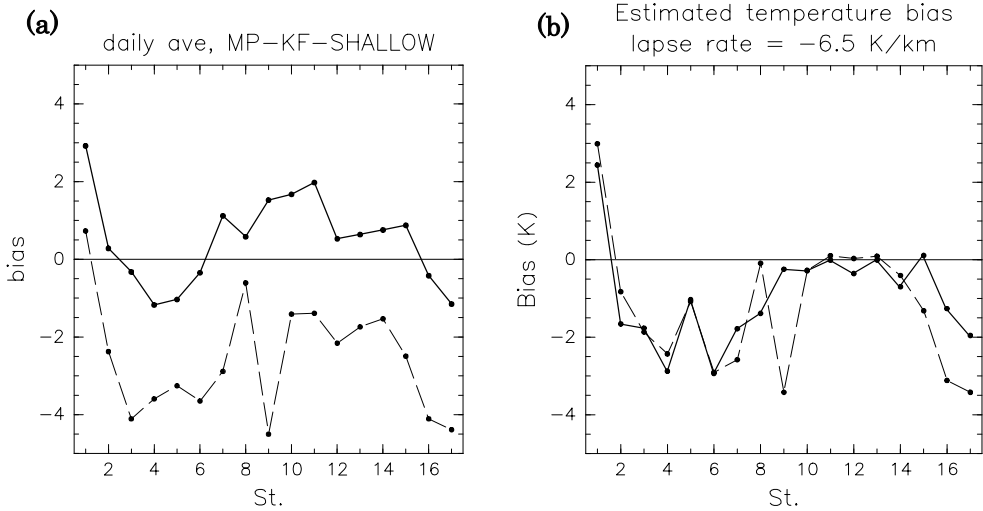


Fig. 6. (a) Bias of daily average surface temperature at 17 stations for MM5 (thick solid line) and NCEP FNL (thin broken line). (b) Same as (a), but estimation from the elevation error with the temperature lapse rate of -6.5 K/km.

stations; the x axis shows the bias of FNL and the y axis shows the bias of the MM5 output. Each panel has 16 points (four years and four months). At station no. 3 and 6, the biases of MM5 output are much smaller than those of FNL. On the other hand, the bias of MM5 is larger than that of FNL at station no. 1. At station no. 1 and 3, time variation of the bias is larger than that at station no. 6. The biases of FNL are much reduced by the downscaling at station no. 3 and 6, while it is increased at station no. 1.

Figure 6a shows surface temperature bias of MM5 output (thick solid line) and FNL (thin broken line) at the 17 stations. At most of the stations, the improvement of the bias by the downscaling is clear. The station-to-station pattern of the bias of the MM5 output is similar to that of FNL. Figure 6b shows the bias estimation at 17 stations calculated from the elevation error of MM5 and that of FNL

with the lapse rate of -6.5 K/km. The station-to-station pattern is almost the same as the actual bias shown in the left panel. From the comparison of the two panels, it is concluded that in addition to the bias due to the elevation error, MM5 has positive bias of about 1 K, while FNL has negative bias of about -2 K.

6. Concluding remarks

We performed downscale experiments on numerical weather predictions in Indochina region using a fine-mesh mesoscale regional model for June, July, August, and September in the wet season of Southwest Monsoon period in 2003, 2004, 2005, and 2006. We evaluated the results using daily average surface temperature observed at 17 stations in Lao PDR.

We employed scatter diagrams of correlation

values to split the effect of the inaccuracy of NCEP Global Final Analyses FNL and the improvement by the downscaling. The month-to-month variation of the improvement rate of the surface temperature is clear; the percentage of the improvement is the highest in September. In July, both the MM5 outputs and FNL have high correlation with the observations, though the rate of the improvement is lower than that in September. In June and August, the correlation between the observations and the MM5 outputs is lower than that in other two months. This is probably due to the low correlation between the observations and FNL. This month-to-month variation can be explained by the seasonal march of the summer monsoon in Southeast Asia. The year-to-year variation of the improvement rate of the surface temperature also depends on the quality of FNL.

The bias of surface temperature has the station-to-station variation depending on the elevation error in the model. In addition, MM5 has a positive bias of about 1 K, while FNL has a negative bias of about -2 K.

Acknowledgements

Most part of this research was done during the first author was a postdoctoral research fellow at

Department of Geophysics, Kyoto University, supported by the KAGI21 (Kyoto University Active Geosphere Investigations for the 21st Century COE Program), which was approved by the MEXT (Ministry of Education, Culture, Sports, Science, and Technology of Japan). This research is also supported by "International Research for Prevention and Mitigation of Meteorological Disasters in Southeast Asia" under the MEXT Special Coordination Funds for Promoting Science and Technology. The figures were produced by GFD-DENNOU Library (<http://www.gfd-dennou.org/arch/dcl/>).

References

- Thalongsengchanh, P., Hadi, T. W., Niwano, M., Otsuka, S., and Yoden, S. (2006): An experimental numerical weather prediction in Indochina region with a meso-scale model. *Annals of Disas. Prev. Res. Inst., Kyoto Univ.*, Vol. 49, No. B, pp. 459-465.
- Thalongsengchanh, P. and Sokhathammavong, K. (2002): Climatic research for mountainous area and high land in Lao PDR. Technical Report of Department of Meteorology and Hydrology, Vol. 1, pp. 80.

メソモデルによるインドシナ域でのダウンスケール数値天気予報実験

Palikone THALONGSENGCHANH*・**・大塚 成徳*・余田 成男*

*京都大学大学院理学研究科

**ラオス水門気象局

要 旨

全球数値天気予報モデルによって「完璧な天気予報」が為されたという仮定の下で、高解像メソスケール領域モデルを用いてインドシナ地域においてダウンスケールハインドキャスト実験を行った。実験は雨季である6月～9月について2003年～2006年の4年間に対して行い、実験結果の検証にはラオスの地表観測点17点の気温を用いた。ここでは散布図を用いて観測との相関係数やバイアスの改善を評価する方法を提案する。観測とモデル結果の相関係数は7月と9月に高く6月と8月に低かった。バイアスは各地点の地形表現の誤差に伴うバイアスに加えて領域モデル結果においては全地点において約1 Kのバイアスが見られた。

キーワード: 数値天気予報, インドシナ地域, メソスケールモデル, ダウンスケーリング