Statistical Downscaling of Rainfall using Large-Scale Predictors: Dynamic Model Outputs vs. Reanalysis Data

Y. Lu[1], P.V. Mandapaka[1], C.C. Kuo[3], T. Y. Gan[3], X.S. Qin[1,2*],

1. School of Civil & Environmental Engineering, Nanyang Technological University, Singapore 639798;
2. Institute of Catastrophe Risk Management (ICRM), Nanyang Technological University, Singapore 639798.
3. Department of Civil and Environmental Engineering, School of Mining & Petroleum Engineering, Faculty of Engineering, University of Alberta, Canada
**Correspondence: Dr. X. S. Qin, School of Civil & Environmental Engineering, Nanyang Technological University, Singapore 639798; Tel: +6567905288; Fax: 67921650; E-mail: xsqin@ntu.edu.sg*

Abstract

A warmer climate is expected to lead to more serious natural disasters, such as heavy storms, prolonged droughts and frequent floods. For a high-density urban region, the flash flood problem may become worse due to possible increasing frequency and magnitude of short-duration rainfalls in the future. A Global Circulation Model (GCM) is a powerful tool to assess the climate change impact. However, the resolution of a GCM output is generally too coarse to be applicable to small regions directly. Two types of approaches, dynamical and statistical downscaling, could be used for bridging the gap between GCM and local climate information. Compared with dynamical downscaling, the statistical approach is more flexible and computationally less intensive. In addition, statistical downscaling tools may be sensitive to the resolution of large-scale predictors. In this study, two downscaling approaches are compared. The first is to use a statistical method (Automatic Statistical Downscaling, ASD) directly to downscale large-scale predictors (i.e. ERA-Interim Reanalysis data) to local rainfall. The second is to combine a dynamical (i.e. MM5) and a statistical method (ASD) to generate the station-level data. The study site is the City of Edmonton and the resolutions of large-scale GCM predictors and dynamical model output are about 150 km and 27 km, respectively. The results show that the downscaled results based on predictors from MM5 is better than that from ERA-Interim, in terms of both accuracy and uncertainty range.

Keyword: statistical downscaling, dynamical downscaling, ASD, MM5

Introduction

Flash floods and urban waterlogging issues which are caused by short-duration heavy rainfalls are serious concerns of many city managers (Dai, 2013). It is also expected that, under climate change impact, more intense extreme events may appear and could lead to escalated damages (Coumou and Rahmstorf, 2012; Benestad et al., 2012). It is thus necessary to develop better modeling and prediction tools for evaluating the impacts of climate change and seeking adaptation strategies. General Circulation Models (GCMs) are powerful tools to provide climate change information for future conditions. There are many GCMs available, such as the HadCM3 (UK Hadley Centre for Climate Model version 3) (Pope et al., 2000) and CCSM3 (The Community Climate System Model, version 3) (Kiehl and Gent, 2004; Collins et al., 2004). However, GCMs are generally of coarse resolutions and their outputs are difficult to be used in prediction or to be coupled with hydrological model in small regions like urban areas (Kharin et al., 2005; Coumou and Rahmstorf, 2012). Over the past decades, dynamical downscaling and statistical downscaling are developed to help generating high resolution climate information from large-scale GCMs (Fowler et al., 2007). The dynamical approach could produce finer resolution climate data based on physical processes, but its computation is rather intensive (Wilby and Wigley, 1997). The statistical downscaling approach is computationally more efficient and easily transferable to different regions. However, it is limited by a lack of physical feedback of climate system and the assumption of stationarity. It is also affected by the selection of predictors, domain size and seasonal variations (Wilby and Wigley, 1997; Fowler et al., 2007). Both approaches have widely applied around the world. Examples can be found in Chandler and Wheater (2002), Hessami et al. (2008), Caldwel et al. (2009), Heikkilä et al. (2010), and Hwang et al. (2011).

Some recent studies showed that the Regional Climate Model (RCM) or dynamical downscaling is weak in providing realistic extreme events (Orskaug et al., 2011; Benestad et al., 2012). Therefore, hybrid approaches, which couple the dynamical and statistical downscaling methods, are proposed. Chen et al. (2012) coupled CRCM (Canadian Regional Climate Model) and the statistical downscaling method (SDSM and Discriminant Analysis with weather typing approach), and indicated that downscaling based on the predictors from CRCM had a significant improvement than those obtained from NCEP reanalysis data. It appears that the coupled method could take the advantages of both dynamical and statistical methods, and may lead to more reliable results. However, there are still limited studies on such a topic and effects of coupling under different conditions need further verifications. Thus, the objective of this study is to examine the resolution effects of large-scale predictors on statistical downscaling of rainfall. The regional climate model, MM5, is applied to dynamically downscale ERA-Interim reanalysis data of 1.5^o x 1.5^o to a 27-km climate data for Edmonton, Canada. Then, a well-known statistical downscaling tool, the Automated Statistical Downscaling

(ASD), is applied based on two different sets of predictors (i.e ERA-Interim and MM5).

Research Methodology

In this study, two downscaling routes are applied: (i) statistical downscaling from large-scale predictors of ERA-Interim to local stations; (ii) statistical downscaling from the output of regional climate model (MM5) to local stations. The detailed descriptions of dynamical and statistical methods are given as follows. Figure 1 shows the framework of research methodology.

MM5 (Dynamical downscaling)

The dynamical downscaling model for this study is based on the MM5 model which is a meso-scale numerical climate prediction system (http://www.mmm.ucar.edu/mm5/). The boundary of MM5 model is driven by ERA-Interim reanalysis data of ECMWF (European Centre for Medium-Range Weather Forecasts). The domains are centered at 51.5^{o}N and 118.0^{o}W. The spatial grid resolution of MM5 is 27 km, and the total number of grids is 76 (latitude) × 90 (longitude). The temporal resolution of MM5 output is 6-hourly, and it is aggregated to daily for supporting statistical downscaling. Other technical details of MM5 setting could refer to Kuo et al. (2014) and Hanrahan et al. (2014).

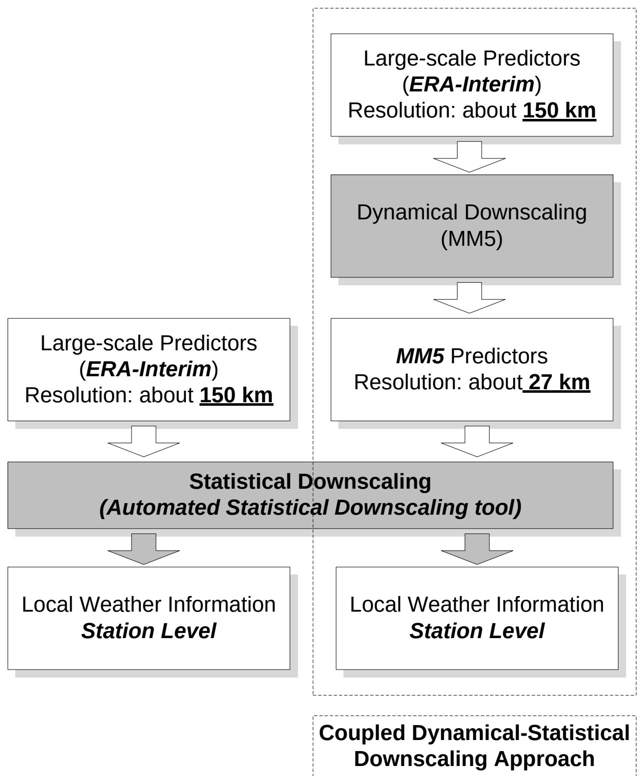

Figure 1. The framework of research methodology.

ASD (Statistical downscaling)

The ASD model is a linear regression-based model, consisting of two sub-models: precipitation occurrence and amount models. They can be described as follows (Hessami et al., 2008).

$$O_i = \alpha_0 + \sum_{j=1}^{n} \alpha_j p_{ij} \quad (1a)$$

$$R_i^{0.25} = \beta_0 + \sum_{j=1}^{n} \beta_j p_{ij} + e_i \quad (1b)$$

where O_i is the daily precipitation occurrence, R_i is the daily amount, p is the predictor, α and β is the model parameters, e is the error. In this model, the error is assumed to follow a Gaussian distribution. Other details could refer to the study of Hessami et al. (2008).

Figure 2. Study area and grid boundary of different predictors (the map is adapted from website http://en.academic.ru/dic.nsf/enwiki/236092).

Study Area and Data

Edmonton is located in central Alberta, Canada (Figure 2). The city has an annual precipitation of about 480 mm. The precipitation is mainly concentrated in summer and the wettest month is July. Therefore, the data from May to August of the period 1984-2010 is used for rainfall downscaling. The rain gauge is located in the central part of the city. The large-scale reanalysis data is based on the ERA- Interim with a $1.5^{o} \times 1.5^{o}$ spatial resolution. The meso-scale dynamical model is MM5, with a spatial resolution at 27 km. The temporal resolution for statistical downscaling is daily. In order to compare two sets of downscaled results fairly, we try to keep the potential predictors (i.e. total input variables) from MM5 and ERA-Interim as consistent as possible. ASD can automatically choose the key predictors based on the backward stepwise regression. Figure 2 also shows the boundaries of different datasets.

Results

In this study, 50 ensembles are generated by ASD for each downscaling route. Figure 3 presents four statistical properties of downscaled rainfall for the month of August, including monthly mean (MEAN), standard deviation (STD), probability of wet day (PWET) and maximum rainfall (MAX). The shown value is the absolute error between the observed data and the average of 50 ensembles. From the figure, MM5 performs better in terms of MEAN, STD and MAX. The ERA-Interim data reproduce the PWET better, but also shows an overestimation as MM5. For uncertainty interval (*UI*), it is evaluated by the equation: $UI = [abs(O_{sim\text{-}upp}-O_{obs})/O_{obs}] + [abs(O_{sim\text{-}low}-O_{obs})/O_{obs}]$, where $O_{sim\text{-}upp}$ and $O_{sim\text{-}low}$ are the upper and lower boundaries of simulated data, respectively, and O_{obs} is the observed data. It is indicated that, MM5 and ERA-Interim demonstrate a similar level of uncertainty interval. Table 1 lists the RMSE and UI for the results for four months. The result based on MM5 shows smaller RMSE values and narrower uncertainty ranges than those based on ERA-Interim. In particular, MM5 predictors could lead to a much higher accuracy in reproducing MEAN using the ASD method. For MAX, MM5 performs as good as ERA-Interim. For different months, MM5 shows a notable better performance for May, June and August, and slightly better performance for July. Overall, the results based on MM5 predictors are superior to those based on ERA-Interim reanalysis data.

Table 1. The RMSE and Uncertainty Interval for simulated results using MM5 and ERA-Interim.

Property	MM5		ERA-Interim	
	RMSE	Uncertainty Interval	RMSE	Uncertainty Interval
MEAN	0.042	0.349	0.299	0.360
STD	0.930	0.417	1.022	0.479
PWET	0.051	0.261	0.078	0.358
MAX	13.750	1.130	13.778	1.209

Conclusions

By comparison, the downscaled results based on predictors from MM5 showed a better performance in reproducing daily rainfall than those based on ERA-Interim reanalysis data. It seems that higher resolution RCM data could potentially improve the statistical downscaling skills in building the relationship of coarse and fine weather variables for urban areas. However, the result was only based on one station and one method, and the data period focused only on the summer season. For future work, we plan to add more stations and statistical downscaling models for a more comprehensive investigation.

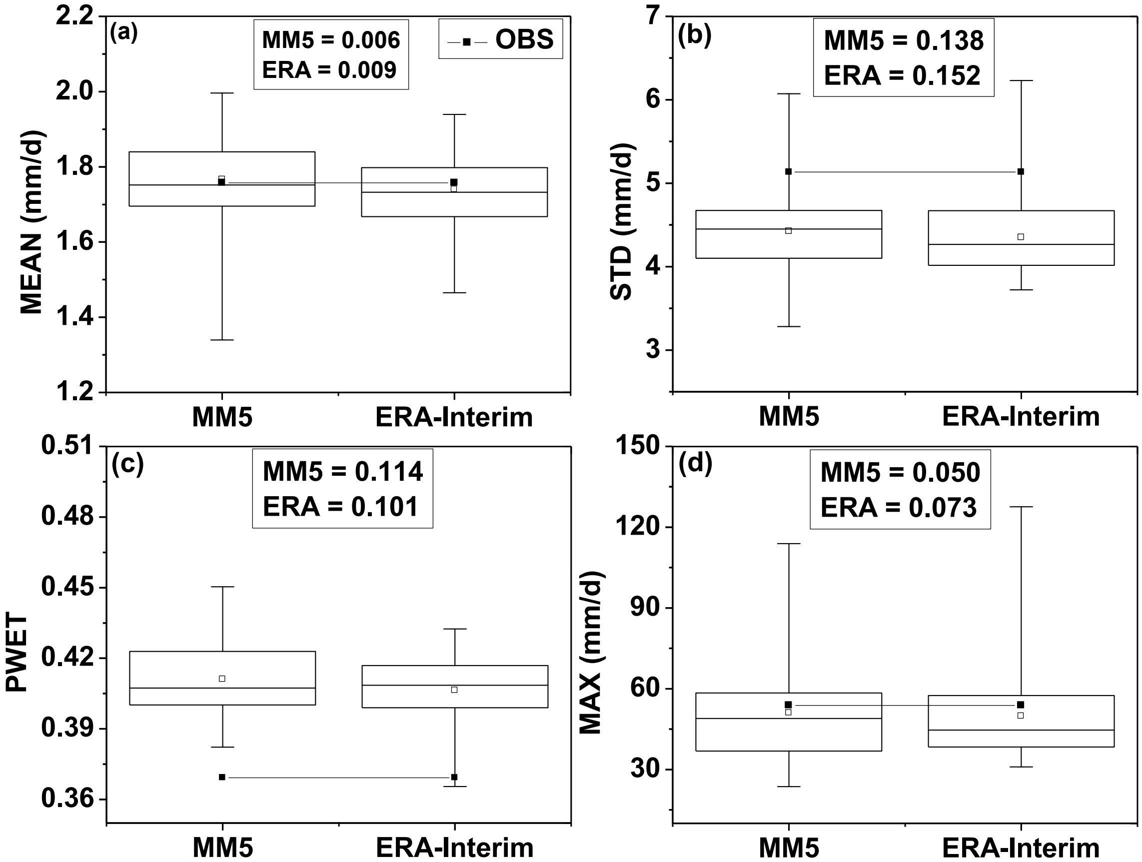

Figure 3. The downscaled results using ASD based on MM5 and ERA-Interim for August. The value shown in the figure is the absolute error between the observed data and the average value of 50 simulated ensembles.

Acknowledgement

This study was supported by Singapore's Ministry of Education (MOM) AcRF Tier 1 Project (M4010973.030) and Tier 2 (M4020182.030) Project. The authors deeply appreciate the data support from the City of Edmonton.

References

Benestad, R.E., Nychka, D., Mearns, L.O. (2012). Spatially and temporally consistent prediction of heavy precipitation from mean values. Nature Climate Change 2, 544-547, doi: 10.1038/NCLIMATE1497.

Caldwell, P., Chin, H.N., Bader, D.C., Bala, G. (2009). Evaluation of a WRF dynamical downscaling simulation over California. Climatic Change 95, 499-521.

Chandler, R.E., Wheater, H.S. (2002). Analysis of rainfall variability using generalized linear models: A case study from the west of Ireland. Water Resources Research 38, 1192, doi: 10.1029/2001WR000906.

Chen, J., Brissette, F.P., Leconte, R. (2012). Coupling statistical and dynamical downscaling for spatial downscaling of precipitation. Climatic Change 114, 509-526.

Collins, W.D., Hack, J.J., Boville, B.A., Rasch, P.J. and others (2004). Description of the NCAR Community Atmosphere Model (CAM3.0). Technical Note TN-464+STR, National Center for Atmospheric Research, Boulder, CO.

Coumou, D. and Rahmstorf, S. (2012). A decade of weather extremes. Nature Climate Change 2, 491-496, doi: 10.1038/NCLIMATE1452.

Dai, A. (2013). Increaseing drought under global warming in observations and models. Nature Climate Change 3, 52-58, doi: 10.1038/NCLIMATE1633.

Fowler, H.J., Blenkinsop. S., Tebaldi, C. (2007). Review Linking climate change modelling to impacts studies: recent advances in downscaling techniques for hydrological modelling. International Journal of Climatology 27, 1547-1578.

Hanrahan, J., Kuo, C. C., and Gan, T. Y. (2014), Configuration and validation of a mesoscale atmospheric model for simulating summer rainfall in Alberta, Int. J. of Climatology, RMS, DOI: 10.1002/joc.4011.

Hessami, M., Gachon, P., Ouarda, T.B.M.J., St-Hilaire, A. (2008). Automated regression-based statistical downscaling tool. Environmental Modelling & Software 23, 813-834.

Heikkilä, U., Sandvik, A., Sorteberg, A. (2010). Dynamical downscaling of ERA-40 in complex terrain using the WRF regional climate model. Clim Dyn, doi: 10.1007/s00382-010-0928-6.

Hwang, S., Graham, W., Hernández, J.L., Martinez, C., Jones, J.W., Adams, A. (2011). Quantitative spatiotemporal evaluation of dynamically downscaled MM5 precipitation predictions over the Tampa Bay Region, Florida. J. Hydrometeor, 12, 1447–1464. doi: http://dx.doi.org/10.1175/2011JHM1309.1

Kiehl, J.T., Gent, P.R. (2004). The Community Climate System Model, version 2. Journal of Climate 17, 3666-3682.

Kharin, V.V., Zwier, F.W., Zhang, X. (2005). Intercomparison of near-surface temperature and precipitation extremes in AMIP-2 simulations, reanalysis, and observations. Journal of Climate 18, 5201-5223.

Kuo, C.C., Gan, T.Y., Hanrahan, J.L. (2014). Precipitation frequency analysis based on regional climate simulations in Central Alberta. Journal of Hydrology 510, 436-446.

Orskaug, E., Scheel, I., Frigessi, A., Guttorp, P., Haugen, J.E., Tveito, O.E., Hang, O. (2011). Evaluation of a dynamic downscaling of precipitation over the Norwegian mainland. Tellus 63A, 746-756.

Pope, V.D., Gallani, M.L., Rowntree, P.R., Stratton, R.A. (2000). The impact of new physical parameterizations in the Hadley Centre climate model – HadAM3. Climate Dynamics 16: 123-146.

Wilby, R.L., Wigley, T.M.L. (1997). Downscaling general circulation model output: a review of methods and limitations. Progress in Physical Geography 21, 530-548.

Wilby, R.L., Dawson, C.W., Barrow, E.M. (2002). SDSM-a decision support tool for the assessment of regional climate change impacts. Environmental Modelling & Software 17, 147-159.