International Conference on Water Resources (ICWR 2009)
26 – 27 May 2009 | Bayview Hotel, Langkawi, Kedah, Malaysia

"OVERVIEW OF SELECTED CLIMATE MODELS IN FLOOD FORECASTING"

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Abstract

The combined use of temporal meteorological data and spatial variability in flood forecasting has not been fully explored. The distribution of meteorological variables such as rainfall, temperature, pressure, humidity and wind is of particular significance in hydrological modelling. This paper reviews the various selected climate models using meteorological data for use in the development of climate model for flood forecasting. Previous study showed that there are several different climate models used in flood forecasting but models had demonstrated different approaches in different areas. Other differences include the use of spatial model and ground gauging station for the estimation of rainfall that are significant in some areas but not in others. Only a few studies have made comparison between selected climate models with other methods of design flood forecasting. However no significant studies have been made in bridging the communication gap between meteorological data using ground gauging station and spatial model that would facilitate flood simulation for a specific range of observation. This overview provides a valuable source for the understanding of the possibility and performance of the use of climate model using both temporal and spatial variability for flood forecasting.

Keywords: Climate model; Meteorological data; Flood forecasting.

1. Introduction

Climatic changes associated with increasing atmospheric concentrations of greenhouse gases are expected to cause changes in the mean conditions of climate, thus, the change in the variability of climate, with extreme events are expected to become more frequent. The damaging nature of extreme events such as storms, heavy rain, droughts and heat-waves is an issue of considerable concern, prompting a recent surge in research into potential changes in climatic extremes and variability.

Assessment of climate change on hydrology requires time series meteorological variables for specific catchments or locations at daily or higher resolution (Kilsby *et al.*, 2007). Data are needed for both the current climate and a range of future possible scenarios. Hydrological models have the potential to provide the necessary information, with adequate climate (rainfall, evaporation, etc.) input information otherwise it is extremely difficult to establish the required models. The integration of meteorological data and the spatial model is still limited to estimating rainfall or developed rainfall equation. Communication gap between meteorological and spatial models is a challenge to weather forecaster.

In recent years, the impacts of extremely heavy rainfall can have on people and communities have been highlighted by events throughout the country. The severe impacts of events demonstrate the importance of research into the variability and extremes of rainfall in present and future climate. To date, however, no rainfall model has incorporated the ability to modify internal weather class properties to stimulate changes which may be occurring (Fowler *et a*l., 2000). It is important to determine the accuracy of rainfall that contributes significantly to the tropical rainfall in order to understand the water cycle.

Meteorology can be divided into distinct areas of emphasis depending on the temporal scope and spatial scope of interest. Rainfall consists of both temporal and spatial variability. Both the temporal and the spatial variability are the elements of rainfall estimations. The contribution factors for temporal variability are by the climatic factors governing rainfall like wind, atmospheric humidity, land and seas temperatures and global circulation patterns. Ordinary spatial variability is because of landscape topography and the climatic variables. In the modern world, these climatic parameters including rainfall, temperature, humidity, pressure and wind can be recorded by meteorological stations on the ground using rain gauge, thermometer, anemometer and other equipment. With regards to rainfall estimation, rain gauge is crucial in determining the rain rate. Rain gauge supports temporal resolution, but unable to support the quality of spatial resolution. Accurate rainfall prediction for temporal variability is difficult within a region or catchment (Tapp *et al.*, 1985). The reason being temporal variability has large variations in space and time (Islam *et al*., 2005).

All historic data are a lack of ground based meteorological data; therefore, the other alternative is to use satellite based monitoring such as radar, infrared channel, remote sensing and other model. This entire tool provides good spatial resolution. The spatial distribution of atmospheric variables such as rainfall served as input in distributed hydrological models and past research has facilitate the interpolations for different geographical locations and for different time period (Carrera-Hernadez and Gaskin, 2007). The advantage of the spatial model such as satellite rainfall model is this model estimates enormous potential benefits as input to hydrological and agricultural models because of their real time availability, low cost and full spatial coverage (Teo and Grimes, 2007).

This paper provides an overview of selected climate models that is pertinent to development of rainfall model. Review on the technique used for model development parameters used as predictors and applications of the models are presented.

2.0 Review of Selected Climate Models

Most researches use rainfall or precipitation data to model climate variation. Other meteorological parameter has been not considered as an important indicator to development of climate model. In 1982, Coe and Stern undertook project to fit models to daily rainfall data acquired from a number of sites with different rainfall patterns. The studies by Tapp *et al* (1986) used rainfall parameters and meteorological parameter to develop model output statistics technique that produce forecast of both the probability of precipitation and the rain amount for 7 major Australian cities in subtropical and middle altitudes.

In the millennium era, Fowler *et al* (2000) develop a regional stochastic rainfall model based on a weather type approach with a spatial element. A daily rainfall data from 150 rain gauges for the period 1961 to 1990 were used as an analysis parameter. Another research was using rainfall data from radar in the analysis is Ekstro *et al* (2004). This analysis uses the future rainfall model as predicted from the UK Meteorological Office, HadRM2 and HadRM3H. The results provide an approach used for impact assessments related to future changes in extreme rainfall in the UK. Fowler *et al* (2004) also uses rainfall data from radar to estimate present extreme rainfall distributions, showing good predictive skill in estimating the statistical properties of extreme rainfall during the baseline period 1961 – 1990.

Fujibe *et al* (2006) noted that the difficulty in detecting change in extreme precipitation is due to lack of data with sufficient time resolution of considerable period. The data used for analysis had many missing and doubtful records arising from errors in the digitalization. In this study, long term changes in the intensity and frequency of heavy precipitation in Japan were analyzed using quality checked daily precipitation data at 51 stations from 1901 to 2004. It shows that, the increase in dry weather events in Japan may be attributed to global warming. Nevertheless, further investigator is required.

In China, during the past 50 years, there have been frequent extreme precipitation events causing severe floods and affecting the economy and environment. The fast growing population and industrialization in major river basins in China in the recent decades appear to have elevated the damage potential of extreme precipitation. Feng *et al* (2007) analyze the variation of extreme precipitation in China using daily precipitation in mainland China for the period 1951 to 2000. The dataset contain 726 stations that have long term precipitation observations. The results indicate that, the changes in extreme precipitation in eastern China are associated with the change in the East Asian Summer Monsoon.

The latest research on temporal and spatial variability had suggested the use of linear and quadratic expressions. The above was found to be able to reduce the bias between the fitted and simulated probabilities of both dry hours and dry days as used in calibration (Burton *et al.*, 2008). Rainfall from rain gauge data and sampled from spatial – temporal Neyman – Scott rectangular pulses process was selected for the applications.

Araki *et al* (2006) was investigating diurnal variation of wind in the rainy season to clarify the existence and structure of local circulation when diurnal variation of convective cloud activity is prominent. The meteorological parameter that observed in this study is wind, cloud and temperature.

Combination of minimum and maximum temperature, rainfall data and daily climatology data to simulate hydrology processes at a daily or hourly time step was used as an observed data (Carrera and Gaskin, 2007). This study examines whether or not the relationship between 3 different climatologically variables and elevation should be used when interpolating daily climatologically data.

In the same year, Kilsby *et al* (2007) develop a weather generator for use in climate impact assessments of agricultural and water system management. It produces series at a daily time resolution using meteorological parameter such as rainfall, temperature, humidity, wind and sunshine for the period 1958 to 2002.

Dunne *et a*l (2008), examine the impact of predicted climate change on hydrology in Ireland. Data for rainfall, temperature and stream flow were used to produce dynamically downscaled precipitation and temperature data. Dunne *et al* (2008) suggest improvements to calibration procedure could be made and examine whether sampling a larger portion of parameter space through a larger initial ensemble size could produce improved calibrations.

New models and systems are still appearing in the literature, which is evidence of a dynamic and developing field of hydrology. Figure 2.1 summarizes the different studies of climate models in different areas and approaches. Table 2.1 shows the overview of the selected climate models with identifications made on the primary and secondary indicators used by the investigators.

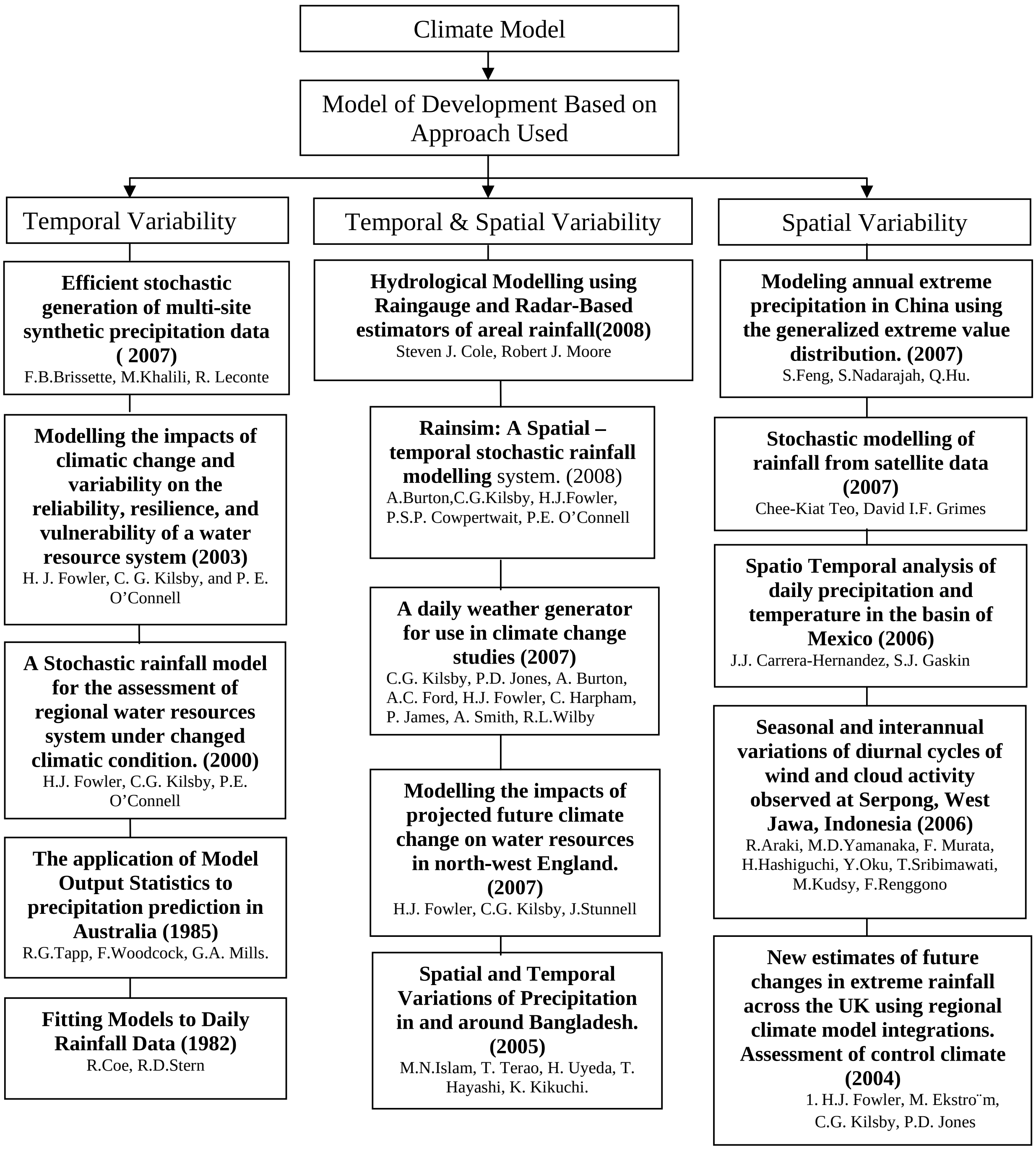


Figure 2.1: Studies on Selected Climate Models for Flood Forecasting

Table 2.1: Overview of the Selected Climate Model

Investigators	Model @ Method	Parameter used in Analysis	
		Primary Indicators	Secondary Indicators
R.Coe, R.D.Stern (1982)	Illustrated by fitting first and second order Markov Chains in transition probabilities vary with time, Gamma Distributions.	Rainfall data and dry data	
R.G.Tapp, F.Woodcock, G.A. Mills (1985)	The model Output Statistics(MOS) technique	Atmospheric Pressure, Air temperature, Wind, Cloud Amount, Rainfall	
H.J. Fowler, C.G. Kilsby, P.E. O'Connell (2000)	A semi Markov Chains model and The Neyman-Scotts Rectangular pulses (NSRP) model.	Daily rainfall data.	
H. J. Fowler, C. G. Kilsby, and P. E. O'Connell (2003)	Combination of a semi-Markov based weather generator to the Neyman Scott Rectangular Pulses (NSRP) stochastic rainfall model and a simplified version of the Arno hydrologic model using Theissen polygons, and PE data	Rainfall amount, Rainfall variability and Potential evapotranspiration	Water resource (Reservoir, river flow)
F.P.Brissette, M.Khalili, R.Leconte (2007)	Stochastic generation of Multi-site Precipitation data following the Wilks approach.	Rainfall	Elevation
H.J. Fowler, M. Ekstro¨m, C.G. Kilsby, P.D. Jones (2004)	Regional frequency analysis and individual grid box analysis.	Rainfall data from radar.	
R.Araki, M.D.Yamanaka, F. Murata, H.Hashiguchi, Y.Oku, T.Sribimawati, M.Kudsy, F.Renggono (2006)	Observation from Boundary Layer Radar	Wind Cloud Activity Temperature	Topography
Chee-Kiat Teo, David I.F. Grimes (2007)	A stochastic calibration, TAMSAT rainfall algorithm, Satellite – base rainfall estimates (SRFE), geostatistical sequential simulation, and 'double kriging' approach adapted to block kriging.	Daily rainfall from satellite based rainfall monitoring.	Cloud top temperature

J.J. Carrera-Hernandez, S.J. Gaskin (2006)	The interpolation method using: 1. Ordinary Kriging (OK) 2. Kriging with external drift (KED) 3. Block Kriging with External Drift (BKED) 4. Ordinary Kriging in a local Neighbourhood (OK1) 5. Kriging with external drift in a local neighbourhood (KED1)	Minimum & maximum temperature. Daily Rainfall.	Elevation @ Topography area
S.Feng, S.Nadarajah, Q.Hu. (2007)	Generalized extreme value (GEV) distribution, The GEV distribution also modified to explore the temporal non-stationary in extreme precipitation events.	Daily precipitation	Location of station
M.N.Islam, T. Terao, H. Uyeda, T. Hayashi, K. Kikuchi. (2005)	The distribution of rainfall obtained by the radar is checked by comparison with that obtained by rain gauge network over the country.	Rainfall amount from rain gauges, Radar data in 10 km grid boxes for daily rainfall and Infrared channel - 1 images.	Cloud activity, wind
H.J. Fowler, C.G. Kilsby, J.Stunnell (2007)	The Mospa Water Resource Model	Daily rainfall and Temperature	Water resource (Lakes, river flow)
C.G. Kilsby, P.D. Jones, A. Burton, A.C. Ford, H.J.Fowler, C.Harpham, P. James, A. Smith, R.L.Wilby (2007)	Stochastic models of rainfall and weather. (Sophisticated Neyman-Scott point process model), Generated in a GIS combining multiple regression with inverse distance-weighted interpolation.	**a)** 5 km x 5 km gridded datasets of mean temperature, daily temperature range, rainfall, sunshine, cloud, and wind speed. **b)**Daily rainfall for the period 1958- 2002. **c)**The 1961-1990 period is taken as a climatological normal for rainfall	Vapour pressure, topography
A.Burton,C.G.Kilsby, H.J.Fowler, P.S.P. Cowpertwait, P.E. O'Connell (2008)	The log parameter Shuffled Complex Evolution (lnSCe) algorithm, Spatial–Temporal Neyman– Scott Rectangular Pulses (STNSRP) stochastic rainfall generator	Rainfall	
Steven J. Cole, Robert J. Moore (2008)	Gridded multiquadric surface fitting techniques, raingauge data, weather radar rainfall data and raingauge-adjusted radar rainfall data.	Rainfall	River flow

Figure 2.2 through 2.12 show the performance of the various methods or model by selected investigators. (R.Coe *et al* (1982); R.G.Tapp, *et al* (1985); H.J. Fowler, *et al* (2000); H. J. Fowler, *et al* (2003); H.J. Fowler, *et al* (2004); J.J. Carrera-Hernandez, *et al* (2006); Chee-Kiat Teo, *et al* (2007); M.N.Islam, *et al* (2005); C.G. Kilsby, *et al* (2007); A.Burton *et al* (2008); Steven J. Cole, *et al* (2008)).

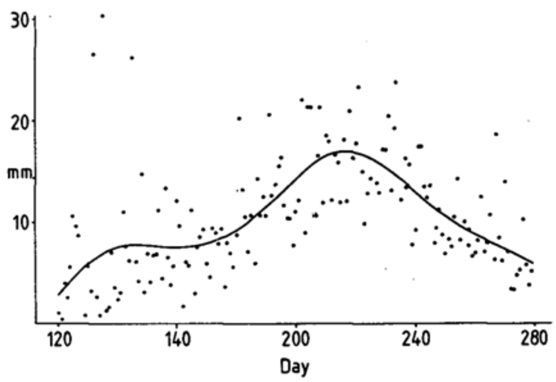


Figure 2.2: Mean rain per rain day at Zinder, Nigeria. Fitted Fourier curve with three harmonics and observed values. R. Coe *et al* (1982).

The result from R. Coe *et al* (1982) is no longer a generalized linear model (GLM) thus the procedures used for estimating the parameters must be modified.

Figure 2.3 shown the reliability of 24 – 48 hours Model Output Statistics (Probability of Precipitation) forecasts by R.G.Tapp *et al* (1985), as indicated by the frequency of occurrence of "rain" and "no rain" days in various probability ranges. Data are shown for both development and independent data for seven cities combined. The resultant forecast therefore had characteristics closely matched to the local climatology at each location.

H.J.Fowler *et al* (2000) developed a weather type precipitation model for use in

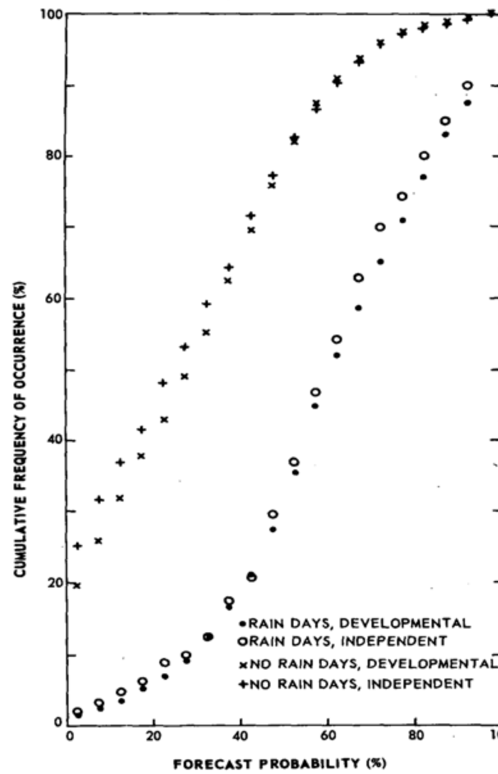


Figure 2.3: The reliability of 24 – 48 hours Model Output Statistics (Probability of Precipitation) forecasts. R.G.Tapp *et al* (1985).

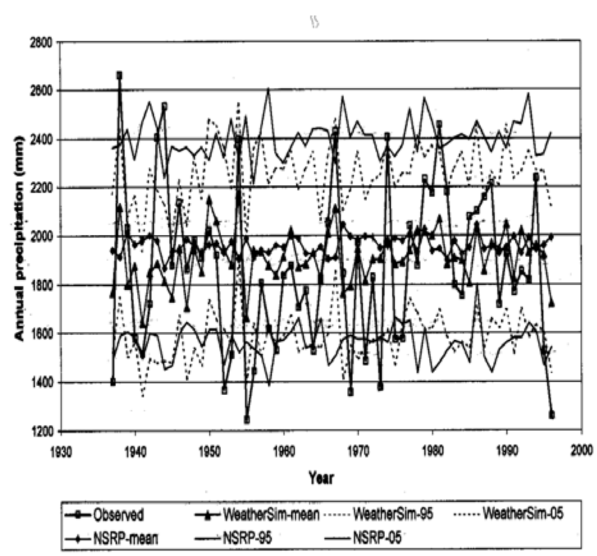


Figure 2.4: Comparison of simulated annual precipitation totals at Moorland Cottage for 1937 – 1996 using the NSRP

model and Weather Sim showing 5 and 95 percentiles. H.J. Fowler, *et al* (2000).

Result from figure 2.4 allows years to be simulated containing high totals generated with equal probability in all months or days.

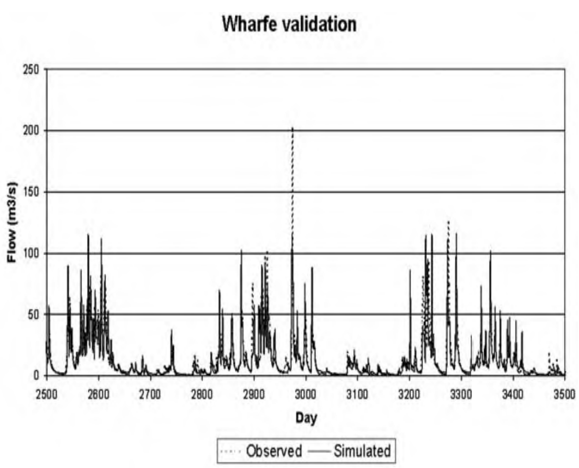


Figure 2.5: The River Wharfe validation sequence from day 2500 to day 3500, showing observed and simulated daily flows. H.J. Fowler, *et al* (2003).

From the study by H.J. Fowler, *et al* (2003), the model produced R^2 values in excess of 0.7 and a satisfactory water balance, defined as ±5%, for all reservoir and river catchment models. The result shows that natural climatic variability plays a large role in the frequency and magnitude of drought events within Yorkshire and elsewhere in the UK. Under a low phase NAO scenario, summer rainfall across the UK is increased and there is reduced seasonality. This causes a significant improvement in both supply reliability and vulnerability when compared to the baseline.

In another study H.J. Fowler, *et al* (2004) has found that the HadRM3H model may be used with some confidence to estimate present extreme rainfall distributions, showing good predictive skill in estimating the statistical properties of extreme rainfall during the baseline period, 1961–1990. Figure 2.6 shows the results for the 10- and 50-year return period magnitudes using the 1-and 10-day event.

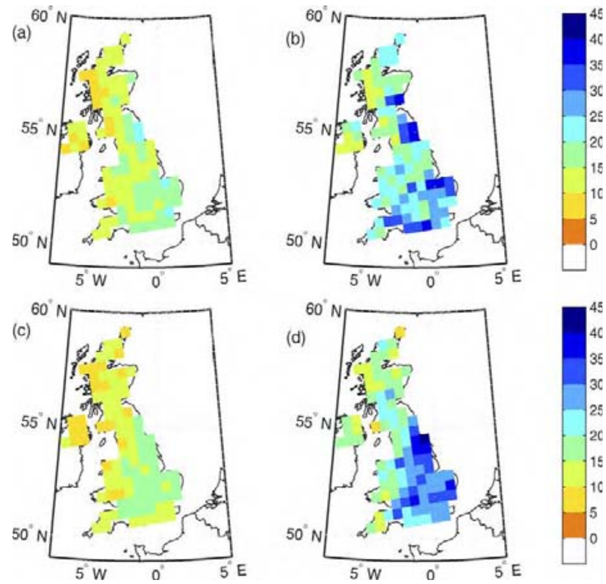


Figure 2.6: Uncertainty in return period estimates for the HadRM3H model using the bootstrap simulation method for the one-day event (a) 10-year return period and (b) 50-year return period and the10-day event (c) 10 year-return period and (d) 50-year return period. H.J. Fowler, *et al* (2004).

Chee-Kiat Teo, *et al* (2007) found that one advantage of stochastic method is that the ensemble of fields can be used as direct input to downstream models to allow realistic sensitivity testing of such models to the uncertainty in the rainfall input.

Alternatively, relevant uncertainty statistics can be calculated from the ensemble pdf at any desired spatial scale. Figure 2.7 shows a comparison between mean satellite rainfall estimates and gauge rainfall.

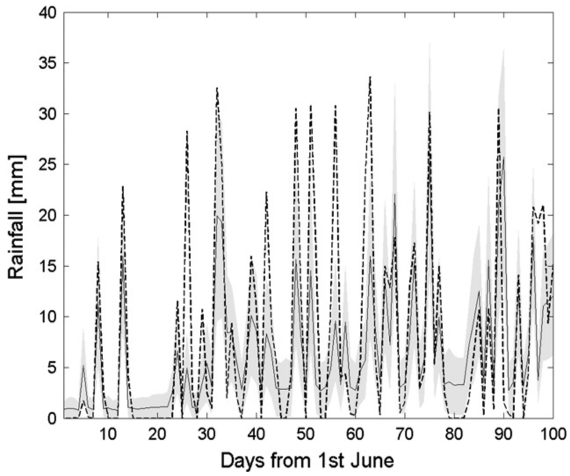


Figure 2.7: Divisional daily rainfall time series for North Bank Division for the first 100 days from 1st June 2001. Legend: Solid line: Mean satellite rainfall estimates; Dashed line: Gauge rainfall estimates. Grey area is bounded by the 16th and 84th percentiles obtained from TAMSIM. Chee-Kiat Teo, *et al* (2007)

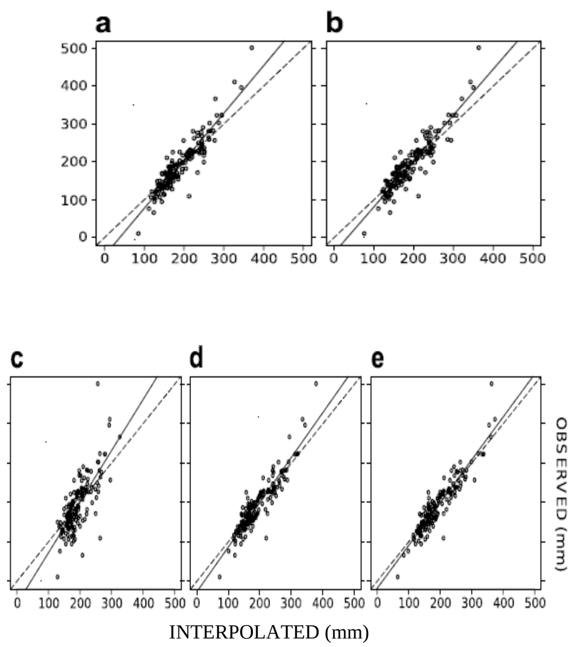


Figure 2.8: Comparison between measured accumulated monthly rainfall and monthly accumulated rainfall derived from daily interpolated rainfall for June 1985 using: (a) Ordinary Kriging; (b) Kriging with External Drift; (c) Block Kriging using External Drift; (d) Ordinary Kriging in a local neighborhood and (e) Kriging with External Drift on a local neighborhood. J.J.Carrera – Hernandez *et al* (2006).

Figure 2.8 above shows one of the results by J.J.Carrera – Hernandez *et al* (2006). In this study, the use of elevation as a secondary variable improved the spatial variation of all climatological fields even when they exhibited low correlation with elevation.

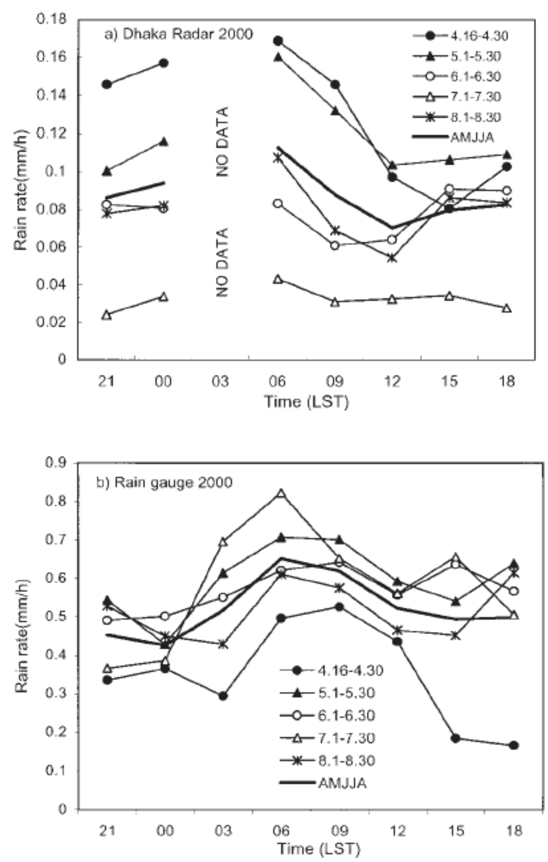


Figure 2.9: Rain rate (mm/h) determined by (a) Dhaka radar and (b) Rain gauge at different hours in different months of 2000. M.N Islam *et al* (2005)

Figure 2.9 shows the distribution of rainfall obtained by the radar, checked by comparison with that obtained by rain gauge network over the Bangladesh. M.N.Islam *et al* (2005) found in the study that the rain distribution obtained by the radar and the rain gauges were similar, while the time of maximum rainfall determined by the radar slightly differed from that determined by the rain gauges.

C.G.Kilsby *et al* (2007) found that a combination and implementation of models, data and methodology is capable of generating self-consistent series of meteorological variables. These variables comprise precipitation, temperature, vapour pressure, windspeed, and sunshine hours. Figure 2.10 shows an assessment of performance in estimating extreme values which are not explicitly used in the fitting procedure. It can be seen that the NSRP model performs better than the Markov model which overestimates the annual maxima, generating some unrealistically large values.

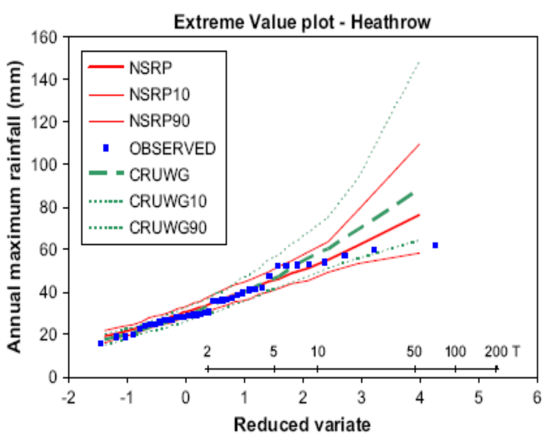
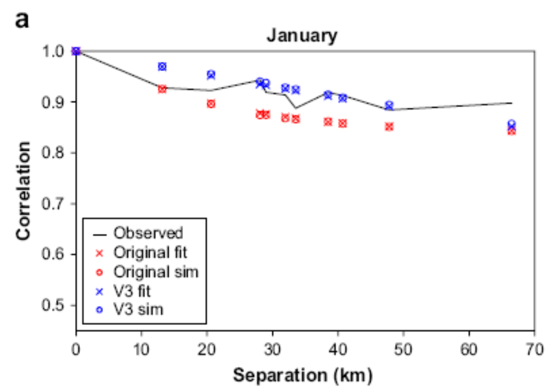


Figure 2.10: Extreme value plot of annual maximum rainfall for Heathrow. 100 series of 30 years data were generated for each rainfall model (NSRP and CRU WG) and the 10 percentile, mean and 90 percentile curves plotted. The CRU WG rainfall model underestimates the observed maxima at higher return periods, and the high upper bound indicates that some unrealistically large maxima are being generated. C.G.Kilsby *et al* (2007)

Result from A. Burton *et al* (2008), the V3 fit was achieved with a single application of the new optimization routine and makes a reasonable overall match to all of the observed statistics used in the fitting. There is also an improvement in the quality of the fit, compared with the Original fit, particularly in the January and December skewness coefficient and spatial correlation statistics. Figure 2.11 shows the cross-correlation between daily time series of all pairs of sites plotted against separation distance for 2 months from different seasons exhibiting the most extreme spatial correlation scales.



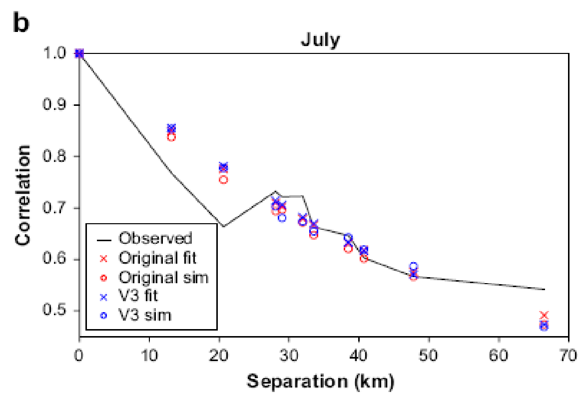


Figure 2.11: Comparison of the spatial cross-correlation with distance relationships for the Original and the V3 fits, for (a) January and (b) July. Observed, fitted (fit) and simulated (sim) cross correlations are shown, each value corresponding to a pair of sites from the five site Dommel catchment. A. Burton *et al* (2008).

S.J.Cole *et al* (2008) used a Gridded multiquadric surface fitting technique to combine the spatial rainfall estimates provided by radar data with the more quantitatively accurate point estimates of rainfall made by raingauge networks. Figure 2.12 shows a result from the model simulations over the calibration period and it also confirm the rather good performance of the raingauge-only estimator and provide a tough benchmark for other rainfall estimators to beat.

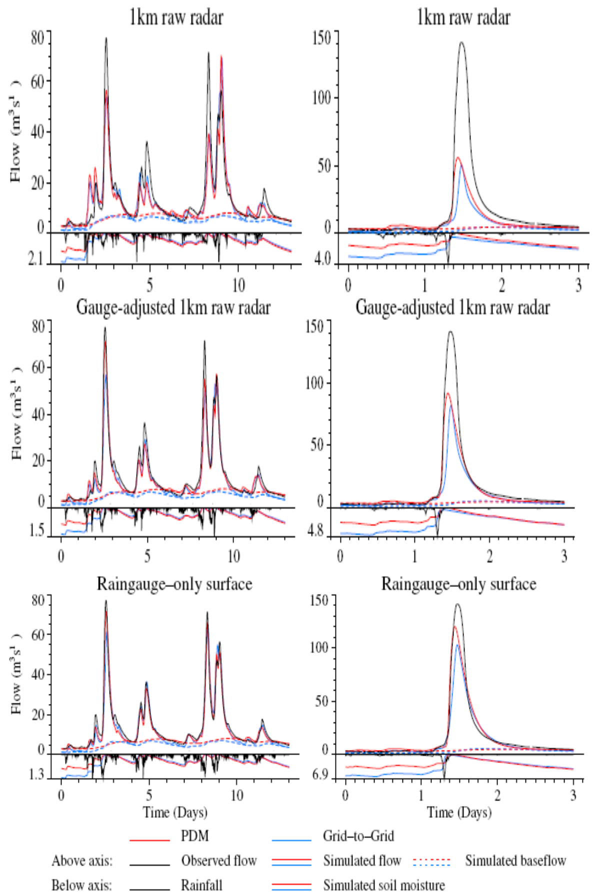


Figure 2.12: Hydrographs for the Darwen catchment using different rainfall estimators and hydrological models for the calibration period 17 February to 2 March 2002 (left column) and the evaluation period 13–16 June 2002 (right column). The figure below the axis is the maximum 15 min catchment average rainfall. S.J.Cole *et al* (2008).

3.0 Summary and Conclusion

Some significant developments are evident on the combined use of temporal meteorological data and spatial data for use in rainfall prediction. However more studies and test need to be carried out on the significance of secondary variables that may have significant effects on the prediction for rainfall.

Future developments will see the inclusion of these variables if deemed significant to the prediction of rainfall. It is the aspiration of the engineers and modellers to be able to put up a climate model that could accurately predict the amount of rainfall that falls on the ground. The successful development of such models would facilitate the relevant agencies in making accurate and reliable predictions for rainfall.

References

1. Kilsby, C.G., Jones, P.D., Burton, A., Ford, A.C., Fowler, H.J., Harpham, C., James, P., Smith, A., Wilby, R.L., 2007. A daily weather generator for use in climate change studies. Journal of Environmental Modelling & Software 22, 1705 – 1719.
2. Carrera-Hernandez, J.J., Gaskin, S.J., 2007. Spatio Temporal analysis of daily precipitation and temperature in the basin of Mexico. Journal of Hydrology 336, 231 – 249.
3. Dunne, S.S., Lynch, P., Mcgrath, R., Semmler, T., Wang, S., Hanafin, J., Nolan, P., 2008. The impacts of climate change on hydrology in Ireland. Journal of Hydrology 356, 28 – 45.
4. Teo, C.K., Grimes, D.I.F., 2007. Stochastic modelling of rainfall from satellite data. Journal of Hydrology 346, 33 – 50.
5. Burton, A., Kilsby, C.G., Fowler, H.J., Cowpertwait, P.S.P., O'Connell, P.E., 2008. Rainsim: A Spatial – temporal stochastic rainfall modelling system. Journal of Environmental Modeling & Software 23, 1356 – 1369.
6. Islam, M.N., Terao, T., Uyeda, H., Hayashi, T., Kikuchi, K., 2005. Spatial and Temporal Variations of Precipitation in and around

Bangladesh. Journal of Meteorological Society of Japan 83, 21 – 39.

7. Araki, R., Yamanaka, M.D., Murata, F., Hashiguchi, H., Oku, Y., Sribimawati, T., Kudsy, M., Renggono, F., 2006. Seasonal and interannual variations of diurnal cycles of wind and cloud activity observed at Serpong, West Jawa, Indonesia. Journal of Meteorological Society of Japan 84A, 171 – 194.
8. Fujibe, F., Yamazaki, N., Kobayashi, K., 2006. "Long term Changes of heavy precipitation and dry weather in Japan. Journal of Meteorological Society of Japan 84, 1033 – 1046.
9. Feng, S., Nadarajah, S., Hu, Q., 2007. Modelling annual extreme precipitation in China using the generalized extreme value distribution. Journal of Meteorological Society of Japan 85, 599 – 613.
10. Coe, R., Stern, R.D., 1982. Fitting Models to Daily Rainfall Data. Journal of Applied Meteorology 21, 1024 – 1031.
11. Tapp, R.G., Woodcock, F., Mills, G.A., 1986. The application of Model Output Statistics to precipitation prediction in Australia. American Meteorological Society, Monthly Weather Review 114, 50 – 60.
12. Rudolf, B., Hauschild, H., Ruth, W., Schneider, U., 1996. Comparison of Rain gauge analyses, Satellite – based precipitation estimates and forecast model results. Journal of Adv. Space Res. 18, 53 – 62.
13. Fowler, H. J., Kilsby, C. G., O'Connell, P. E., 2003. Modelling the impacts of climatic change and variability on the reliability, resilience, and vulnerability of a water resource system. Journal of Water Resources Research 39, NO. 8, 1222, doi:10.1029/2002WR001778.
14. Fowler, H.J., Ekstro¨m, M., Kilsby, C.G., Jones, P.D., 2004. New estimates of future changes in extreme rainfall across the UK using regional climate model integrations. 1. Assessment of control climate. Journal of Hydrology 300, 212 – 233.
15. Ekstro¨m, M., Fowler, H.J., Kilsby, C.G., Jones, P.D., 2004. New estimates of future changes in extreme rainfall across the UK using regional climate model integrations. 2.Future estimates and use in impact studies. Journal of Hydrology 300, 234 – 251.
16. Fowler, H.J., Kilsby, C.G., O'Connell, P.E., 2000. A Stochastic rainfall model for the assessment of regional water resources system under changed climatic condition. Journal of Hydrology & Earth System Science 4, 263 – 282.
17. Fowler, H.J., Kilsby, C.G., Stunnell, J., 2007 Modelling the impacts of projected future climate change on water resources in north-west England. Journal of Hydrology & Earth System Science 11, 1115 – 1126.
18. Cole, S.J, Moore, R.J., 2008. Hydrological modelling using raingauge and radar based estimators of areal rainfall. Journal of Hydrology 358, 159 – 181.
19. Brissette, F.P., Khalili, M., Leconte, R., 2007. Efficient stochastic generation of multisite synthetic precipitation data. Journal of Hydrology 345, 121 – 133.
20. Lawal, B., Mansor, S., Mahmud, A.R., 2004. Spatial information technology in flood early warning system: an overview of theory, application and latest developments in Malaysia. Journal of Disaster Prevention and Management 13, 356 – 363.