From Risk to Resilience

Working Paper 3

-

71

Downscaling: Potential Climate Change Impacts in the Rohini Basin, Nepal and India

Sarah Optiz-Stapleton (ISET) Subhrendu Gangopadhyay (University of Colorado, Boulder) & The Risk to Resilience Study Team







From Risk to Resilience

Working Paper 3

Downscaling : Potential Climate Change Impacts in the Rohini Basin, Nepal and India

Sarah Optiz-Stapleton (ISET) Subhrendu Gangopadhyay (University of Colorado, Boulder) & The Risk to Resilience Study Team

November, 2008

Please use the following reference for this working paper:

Optiz-Stapleton, S., S. Gangopadhyay and The Risk to Resilience Study Team, (2008): Downscaling : Potential Climate Change Impacts in the Rohini Basin, Nepal and India, From Risk to Resilience Working Paper No. 3, eds. Moench, M., Caspari, E. & A. Pokhrel, ISET, ISET-Nepal and ProVention, Kathmandu, Nepal, 28 pp.

© Copyright, 2008

ProVention Consortium; Institute for Social and Environmental Transition; Institute for Social and Environmental Transition-Nepal.

This publication is made possible by the support of the ProVention Consortium and United Kingdom's Department for International Development (DFID). The research programme is supported through DFID grant number OHM0837, NOAA award number NA06OAR4310081 and the Canadian International Development Research Centre (IDRC) Centre file 103232-001. Views and opinions expressed within do not necessarily reflect the positions of ProVention, IDRC, NOAA or DFID. The findings, interpretations and conclusions expressed in this paper are those of the authors alone.

Any part of this publication may be cited, copied, translated into other languages or adapted to meet local needs without prior permission from ProVention Consortium, ISET or ISET-Nepal provided that the source is clearly stated.

First Edition: 2000 November, 2008.

ISBN: 978-9937-8019-8-0

Series editors: Marcus Moench, Elisabeth Caspari & Anil Pokhrel.

Published by: ProVention Consortium, Institute for Social and Environmental Transition and Institute for Social and Environmental Transition-Nepal.

Cover: On August 18, 2008 the Kosi embankment north of Kosi Barrage breached causing widespread devastation in Nepal and Bihar. Photograph of boats being used to recover possessions. Photo by Anil Pokhrel.

DESIGN AND TYPESETTING Digiscan Pre-press Pvt. Ltd., Kathmandu, Nepal.

PRINTED AT Format Printing Press Pvt. Ltd., Kathmandu, Nepal.

Contents

Introduction	1
Basin Description	5
Data Sets and Assumptions	7
Methodology	11
Climate Diagnostics	11
Statistical Downscaling Model	12
Model Verification	14
Climate Change Projections	17
Summary of Findings	21
Concluding Discussion	21
References	25
Annex I: Working Paper Series	27
Annex II: Acknowledgements	28
0	

Introduction

Floods, droughts and other weather related disasters are a major factor contributing to endemic poverty in regions such as South Asia and this is likely to increase as climate change proceeds. Risk reduction interventions represent a major avenue for responding to both existing flood and drought hazards and the increases likely to emerge as a consequence of climate change. Investments in risk reduction are, however, difficult to economically justify unless their returns can be assessed. Cost-benefit techniques are the primary set of economic tools through which such assessments are currently made. The ability to make such assessments depends, however, on the availability of probabilistic information. We need to know the frequency with which events such as floods and droughts will occur and we need to know the magnitude of such events. Such information is generally not available, particularly at the local level in developing countries where populations are large and particularly vulnerable.

The Rohini Basin, part of the larger Gangetic Basin straddling the border of India and Nepal, is home to some of the poorest populations in the world. Populations in the Nepal Tarai and in the Indian state of Uttar Pradesh are particularly affected (Moench and Dixit, 2004). Social, political and economic factors, in combination with geography, make this basin particularly vulnerable to flooding during the monsoon months. During the 2007 monsoon, over 2 million in Uttar Pradesh were adversely affected by floods through habitat loss, destruction of villages, inundation of cropland and livelihood disruption.

The Intergovernmental Panel on Climate Change (IPCC) (Christensen et al., 2007) estimates that average June-August precipitation throughout South Asia (defined as the region 5°N,64°E to 50°N,100°E) will increase approximately 11%, as will heavy precipitation events by 2099. This is an extremely large area and the general circulation models' (GCMs) projections do not say how the precipitation will be spread throughout the area. Furthermore, such information is often not specific enough to be used in planning and implementing adaptation and disaster risk reduction measures. In order to effectively support such measures, information about potential climate change impacts is needed at smaller geographic scales.

General circulation models are complex computer models that simulate global weather (timescales under 10 days) and climate (anything over 10 days) patterns by modelling the

physical processes and interactions between the land, ocean, and the atmosphere. The horizontal grid resolution of GCMs is typically on the order of 100-200 km, insufficient to capture trends or make projections of potential climate change impacts at smaller scales, such as river basins. Furthermore, there are large discrepancies between the precipitation and temperature estimates derived from the various GCMs utilized by the IPCC (Kripalani et al., 2007; Tolika et al., 2006). However, GCMs generally simulate large-scale climate fields, such as wind and humidity (Trigo and Palutikof, 2001; Osborn et al., 1999) quite well and these climate phenomena can be used to drive models that simulate climate change impacts at smaller geographic scales.

Various downscaling techniques have been developed that attempt to provide forecasts of potential climate change impacts at smaller scales, guided by output scenarios from GCMs (Dibike and Coulibaly, 2005; Gangopadhyay et al., 2005). The techniques range from numerical methods (for example, PRECIS developed by the UK

FIGURE 1 Maps of the Rohini Basin showing basin location across India-Nepal border and gauging stations



Hadley Centre) and statistical techniques. Numerical methods forecast the physical responses of an area (from regional scale to global scale) to various sets of inputs (e.g., soil moisture or greenhouse gas concentrations). Numerical climate models run at any geographic scale require large sets of reliable data; data that may not exist in developing country contexts such as the border region of Nepal and India. Statistical downscaling techniques attempt to establish a statistical relationship between point source (weather station) weather variables, such as precipitation or streamflow, and large-scale climate fields such as wind or air pressure at different atmospheric levels.

Pokhara NEPAL Kathmandu Butwā Bahraich Birgani Faizābād ۲ Motihari Gorakhpu Gandaki River INDIA BIHAR Ganga River UTTAR PRADESH Muzaffarpur 26

The focus of this study is the Rohini Basin, which straddles the border of Nepal and India (Figure 1). Data paucity in this region makes it difficult to employ numerical downscaling techniques, such as PRECIS. Therefore, a robust stochastic technique was developed to generate precipitation ensembles that can be utilized to test climate change scenarios at the river basin level. As with all climate models of any scale, the validity of the model output is determined by the dataset fed into the model. Stochastic models are better able to handle situations in which there is not much data, but the quality of the data determines the model's ability. The old saying of "garbage in, garbage out" is very true of climate modelling.

This paper presents a new statistical technique for downscaling climate information from general circulation models so that this information can be used as an input to economic evaluation of options for reducing flood and drought risks and responding to the impacts of climate change. Other papers in this series (From Risk to Resilience Working Paper Nos. 4 and 5) present cases on the use of this downscaled climate information in the evaluation of risk reduction measures in Eastern Uttar Pradesh (India). We conclude that, although the method presented here can provide key insights, the results must be used with caution: they illustrate the types of changes that could occur as a consequence of climate change but do not represent extremely certain predictions. Furthermore, limitations in the availability, accuracy and accessibility of historical data at the field level often limit the ability to incorporate even robust projections of change in key climate variables in the evaluation of flood and drought event probabilities and thus in the economic analysis of avenues for risk reduction.

Basin Description

The Rohini Basin is relatively small, with a catchment area of 2,701 km² that straddles the borders of Nepal and India (1,943 km² in India and 758 km² in Nepal). The basin lies just south of the Himalayan Range, which rises to 8,000 m in less than 100 km from the basin. Precipitation patterns in the basin are strongly linked with the seasons and falls always as rain (as opposed to snow). While only 30% of the total catchment area lies within Nepal, the majority of the rain that feeds the basin falls within the headwater reaches in Nepal (Dixit et al., 2007). Nearly 90% of the annual precipitation falls from roughly mid-May through mid-September and is associated with the South Asian Monsoon (Figure 2). Occasionally, weak depressions beginning in the Mediterranean bring rainfall to the area during December and January, but this does not happen every year.



| FIGURE 2 | Average annual precipitation in the Rohini Basin

Annual average precipitation cycle in the Nepali side of the Rohini Basin (blue) and for the Gorakhpur District (red). The monsoon season occurs during the months of June-September and corresponds with the peak seen in the figure. The Gorakhpur District rainfall data were sourced from the India Water Portal (2008). The India Water Portal data are derived from interpolated global monthly rainfall data from the Tyndall Centre's CRU TS 2.1 dataset. The TS 2.1 dataset is a grid interpolation of available weather station data. As will be explained in the data section, weather station spacing in this region of India is extremely sparse, and the data incomplete. Therefore, the TS 2.1 dataset can be used to give a rough estimate of annual behaviour on the Indian side of the Rohini Basin, but could not be used in this downscaling effort.

Data Sets and Assumptions

Obtaining daily precipitation data of sufficient historical length for the basin was extremely difficult. ISET-Nepal was able to purchase complete rainfall data for five weather stations in the basin for the period 1976-2006. The validity of the datasets cannot be verified. Furthermore, little information exists on the verification process used to check the data. Thus, there are potentially significant flaws in the Nepali datasets, which cannot be corrected because of lack of information.

Purchasing datasets for Nautanwa and Gorakhpur Airport from the Indian Government was beyond the scope of the budget allocated for this project. We attempted to procure data from the Nautanwa station, but the price set by the Indian Government was 50,000 rupees. In the end, due to cost limitations, no datasets for India were purchased or utilized in the downscaling model.

Supplemental data was acquired for Bhairahawa Airport (Nepal) and Gorakhpur Airport (India) from the National Climate Data Center (NCDC) for the periods of 1977-2006 and 1954-2006, respectively. The NCDC dataset for Bhairahawa Airport was used to fill gaps in the Bhairahawa Airport set compiled by ISET-N and to check the validity of the dataset. The two datasets were strongly correlated at 0.98. Roughly 35% of the NCDC dataset for Gorakhpur Airport were missing and could not be filled using traditional hydrology methods because we had no other datasets for stations in India. Thus, no Indian rainfall stations were included in this modelling effort, which makes it difficult to project potential climate change impacts on the Indian side of the basin. The lack of Indian rainfall data presents a severe limitation of the model's ability to accurately make predictions of potential climate change impacts in the Rohini Basin.

All of the Nepali stations, except Dumkauli, lie within the catchment area. Dumkauli is not in the basin, but it is extremely close and its precipitation patterns are similar to the basin's both in amount and timing. Due to the limited amount of rainfall data and the geographic distribution of rain gauges in the basin, it was necessary to include Dumkauli in model predictions. Less than 3% of the data was missing for any given year from each of the stations over the period of 1976-2006. Daily precipitation values were aggregated to obtain monthly rainfall totals for each of the five stations for the 31-year timeframe. Large-scale climate field predictors for this study were obtained from the NCEP/ NCAR reanalysis archive (Kalnay et al., 1996). Much of the rainfall associated with the monsoon is due to thunderstorm (convective) activity over the basin. Selection of large-scale climate fields is governed by two sets of assumptions that determine the physical relationship between the local variable (rainfall) and the large-scale variables. The first set is based on the necessary atmospheric conditions that allow for convective activity, from which most the Rohini's rainfall is based:

- 1) changes in air pressure that lead to atmospheric instability (measured through geopotential height)
- 2) moist air (measured through specific humidity)
- 3) warm air (measured through air temperature)
- 4) a transport mechanism to move the warm, moist air (measured through winds)

The second set of conditions is governed by their climate change relevance (von Storch et al., 2000):

- 1) the large-scale climate predictors have a direction physical relationship with the local variable and are realistically modelled by the GCMs
- 2) the physical relationship between the large-scale predictors and the rainfall is expected to remain relevant in the future, regardless of climate change
- 3) the large-scale climate predictors capture the climate change signal

We obtained monthly mean large-scale climate variables - geopotential height, zonal or meridional winds, specific humidity and air temperature at different vertical pressure levels for the years 1976-2006. The variables cover the geographic region of 25-30°N and 80-90°E and represent area averaged data over fifteen grid spaces with a 2.5°x2.5° (latitude-longitude) resolution. These datasets can be accessed and analyzed from the National Oceanic and Atmospheric Administration (NOAA) online database at: http://www.cdc.noaa.gov/Timeseries.

The final step in choosing data for a statistical downscaling model is figuring out which GCMs' output to use. The IPCC report synthesizes climate change projections from 22 different GCMs operated by various universities and research centres from around the world. Kripilani et al. (2007) analyzed each of the GCMs to see how well each could replicate important features of the South Asian Monsoon. They investigated each model's ability to reproduce historic inter-annual behaviour, intra-seasonal variability and historic mean precipitation. Only 6 out of the 22 models were able to reproduce historic observations of monsoons from the 20th century. We selected one of these six, the Canadian Third Generation Coupled Climate Model (CGCM3) because of its ability to replicate the South Asian Monsoon and the ease of acquiring output data from this model. Lack of time prevented investigating and using data from the remaining five GCMs.

For this project, the partners decided to use the climate change scenarios A2 and B1. The A2 scenario assumes that population growth and fossil fuel usage will continue to be quite high for a number of years to come, whereas the B1 scenario assumes that the amount of carbon dioxide in the atmosphere will stabilize at around 550ppm. For a more detailed explanation about the IPCC scenarios, refer to the IPCC (2000) special report on Emissions Scenarios. Due to the rapidity with which

the climate is already changing (for example, the faster melting of the Arctic and Greenland ice sheets) and the GCMs' inability to capture these rapid changes, we felt potential climate change scenarios are not likely to be valid beyond 2050. Thus, the downscaling model projects climate change impacts on precipitation in the Rohini Basin only for the period 2007-2050.

Data for the four large-scale climate predictors mentioned above were obtained from the CGCM3 for the period of 2007-2050 over the same geographic range as the NCEP data. The resolution of the CGCM3 data is coarser, with grid divisions of 3.75°x3.75° or only 9 grid squares over the same geographic domain as the NOAA data. The CGCM3 model is run in ensemble mode, that is the model is run five times for a scenario (say A2) using slightly different starting conditions, to generate a small range of possible climate change conditions for a particular scenario and provide a better sense of what uncertainties exist in the model. Thus, we collected CGCM3 output data for 10 different ensemble runs: five runs from A2 and five runs from B1. For the remainder of this document, we refer to these ensemble runs as either A2R# or B1R#, with the # sign indicating runs 1 to 5.

Methodology

Climate Diagnostics

Since the Rohini Basin is not a large basin from a climate variability perspective and the rainfall patterns between the five stations were strongly correlated, the monthly rainfall mean of the five gauges was calculated. This monthly mean was used as the rainfall predictand to train the model over the historical period of 1976-2006 before using the model to make projections of climate change in the basin.

The South Asian Monsoon is an annual pattern of increased rainfall over South Asia, typically beginning around late May and ending in September¹. The monsoon develops when a low-pressure system forms over the Tibetan Plateau and the winter-spring upper-level westerly jet stream over the southern Himalayas disappears. The low pressure causes the winds to shift direction and blow from the southwest over the Indian subcontinent, bringing moisture from several places. The temperature difference between the land and the Indian Ocean also contributes to formation of monsoon thunderstorms. Tropical cyclones and depressions moving through the Bay of Bengal or other parts of the Indian Ocean enhance extreme rainfall events during the monsoon and contribute to severe flooding in the Rohini Basin. The monsoon ends when the Tibetan low pressure breaks down and the upper-level westerly jet resumes, generally during September (Torrence and Webster, 1999; Fasullo and Webster, 2003; Meehl and Arblaster, 2002).

The physical relationships between the large-scale climate indices and the basin rainfall are established using correlation analysis. While correlation does not imply causation, it is well established in meteorology that certain physical processes contribute to the formation of thunderstorms and the monsoon. We performed correlation analysis between each month's rainfall and various large-scale climate features (geopotential height, specific humidity, air temperature, and meridional and zonal winds). See Figure 3 for an example of the correlation analysis. While historically the monsoon has been strongly correlated with snowfall amounts over

¹ The exact timing of monsoon onset and termination depends on the location. For the Rohini Basin, the monsoon typically begins around mid-June and ends mid-September. There is however considerable variation each year.

the Tibetan Plateau and the El Niño Southern Oscillation (ENSO), these relationships are changing and it is not certain what the nature of the relationship will be in the future due to climate change (Saji et al., 2006; de Szoeke and Xie, 2008). Therefore, we decided not to use these large-scale climate features in our modelling efforts. The correlations were tested for significance and the feature that had the highest correlation with the month's rainfall were identified and used to form the predictor set.









The NOAA datasets and the CGCM3 datasets have different grid spacing, which had to be resolved before selection of the final predictor set for the model. In each dataset, the variable (e.g. wind) is measured at the centre of the grid space. The NOAA dataset is comprised of fifteen measurements, one per grid space and the CGCM3 has nine values, one per grid space. Thus, the NOAA dataset needed to be reduced to nine grid points that are spatially matched with the CGCM3 grid spacing. We used the great circle distancing method (a standard geometry technique) to map the NOAA dataset grid points onto the CGCM3 grid spacing.

The final NOAA and CGCM3 datasets contain data from four variables (wind, geopotential height, specific humidity and air temperature). The final data matrix for both contains thirty-six columns (9 columns corresponding to the measurements at 9 grid points per variable). The NOAA dataset contains values from 1976-2006. The CGCM3 dataset is actually comprised of 10 different datasets, five runs from each climate change scenario A2 and B1 for the years 2007-2050.

Statistical Downscaling Model

The goal of the statistical downscaling model is to project how various climate change scenarios will alter precipitation patterns in the Rohini Basin for the years 2007-2050. Since we have no way of testing

the validity of the model's projections in the future, we assess the model's performance by how well it is able to replicate each month's historical precipitation for 1976-2007. This is termed the model calibration or "testing period".

Statistical downscaling methods involve finding a relationship between large-scale climate features and the local feature (e.g. rainfall) to be predicted. There are numerous statistical downscaling techniques in use: (1) regression-based (e.g. neural networks or principal component analysis), (2) classification methods (e.g. weather generators) or (3) analogue methods. The modelling method utilized for this study is robust, simple analogue method run in ensemble mode (Gangopadhyay et al., 2005; Opitz-Stapleton and Gangopadhyay in press). During the model "testing period" of 1976-2006, the model is run in drop-one, cross-validation mode, which is described further below. Each month is hindcast separately to better capture the intra-seasonal rainfall patterns of the Rohini Basin. The model methodology is basically as follows:

 Let [X] represent the matrix of data of large-scale climate indices for n (31) years and m (36) columns corresponding to four variables from nine grid spaces from the NOAA dataset. "cols" = columns.

[X] = [1976 geopotential (9 cols), wind (9 cols), specific humidity (9 cols), air temp (9 cols)]

····

[2006 geopotential (9 cols), wind (9 cols), specific humidity (9 cols), air temp (9 cols)]

- 2) For the year i that we are trying to predict (say rainfall of May 1980), select the corresponding large-scale climate variables of that year i. The variables of this year form the feature vector [F].
- 3) Perform the drop-one cross-validation. This involves dropping the year i we are trying to predict, and all the variables of that year, from the matrix [X] to form a smaller climate variable matrix [S] that is one year less than [X]. The model then tries to make the rainfall prediction from the smaller dataset [S].
- 4) Compare the climate variables from [F] to all the other climate variables from the matrix [S]. Find the years in [S] which have the most similar large-scale climate conditions to [F], keeping only the years that are the most similar to [F]. Let us call this group with the most similar climate conditions the "K-Nearest Neighbours" (K-NN).
- 5) Take the rainfall values for each of the K-NN years as the set of possible rainfall values for year we are trying to predict. Assign each of these rainfall neighbours a weight depending on how close its corresponding climate variables are to the climate variables of year i.
- 6) Bootstrap the K-NN rainfall values according to its weight to generate an ensemble of rainfalls for the year i (Venables and Ripley, 2002). The bootstrapping is performed 30 times to generate 30 ensemble members. For each of the years 1976-2006, repeat steps 2-6 to obtain an ensemble rainfall reconstruction.

The steps are slightly different generating rainfall predictions for the years 2007-2050, conditioned on the climate change scenarios selected from the CGCM3. No drop-one cross-validation is used when forecasting according to climate change scenarios.

- 1) This step is the same as step 1 above.
- 2) The difference between this step and step 2) above is that the feature vector [F] is formed from the CGCM3 dataset. So, [F] is comprised of the large-scale climate

indices projected by the CGCM3 for a single run of climate change scenario A2 or B1.

- 3) The vector [F] of future large-scale climate indices is compared directly with the matrix [X] of historical climate variables derived from the NOAA datasets and the K-NN rainfalls found.
- 4) Steps 5 and 6 are the same, with the model repeated for each year 2007-2050 to generate ensembles.
- 5) The monthly rainfall projections are disaggregated to daily time steps using the daily rainfall percentage distributions from the historical record. For example, say May 2020 had six K-NN (e.g. 1978, 1987, 1992, 1995, 2001, and 2003). In May 1978, rain fell in six days throughout the month, with each day receiving a percentage of the total monthly rainfall. The percentage rainfall patterns were then multiplied by May 2020's monthly rainfall projection to produce hypothetical daily rainfall distributions.

Model Verification

Each ensemble forecast is equally probable for the period 2007-2050. We will not know until the future has become the past which forecast was the most accurate. *We can only test the model's accuracy, and whether or not we chose the correct large-scale climate variables, by seeing how well the model could hindcast the historical rainfalls for 1976-2006.* For the remainder of this paper, we only discuss the monthly ensemble rainfall projections. One method is to visually compare the ensemble rainfalls with the historical rainfalls, such as seen in Figure 4. Boxplots provide a pictorial comparison of the historical rainfall with the model's ensemble rainfalls. Each box represents the numerical range of the rainfall ensembles generated by the model. The bottom "whisker" coming out of the box presents some of the lowest rainfall ensembles and the top "whisker" represents the highest rainfall projections. The box represents the spread of the majority of the rainfall ensembles. The black line in the middle of the box represents the middle value ensemble rainfall. The red triangle represents the actual, historically observed rainfall.







Each month was modelled separately to try to account for the different large-scale climate processes that cause rainfall in each month. Consequently, the model's rainfall predictions are better in some months than in others. If a box (seen in Figure 4) is really narrow and centred around the red triangle, this indicates that the model was relatively "certain" about its rainfall predictions. If the box is relatively wide or the red triangle falls in a "whisker", this indicates that there was a wide range in the large-scale climate conditions and that the model was more "uncertain" about the rainfall prediction.

Another way of measuring the model's performance is to find the correlation between the median (the middle) ensemble member and the observed historical rainfall value. Table 1 displays the correlation between the median ensemble member and the historical rainfall. The model was able to replicate the historic precipitation value better in some months than in others. In general, the median ensemble member is well correlated with observed. During the monsoon months of June-August, the model is able to predict the rainfalls well, except for years in which the rainfall was abnormally high for that month. In cases of really high rainfall, the model has a tendency to underpredict or make lower predictions of rainfall

Month	Correlation Coefficient
January	-0.17
February	0.39*
March	0.65*
April	0.47*
May	0.62*
June	0.33**
July	0.33**
August	0.53*
September	0.22
October	-0.23
November	0.43*
December	0.48*

TABLE 1 Correlation of the median ensemble members with the observed rainfall for each month over the period of 1977-2006

* is significant at the 95^{th} percentile. ** is significant at the 90^{th} percentile.

than actually occurred. The model is underpredicting these high rainfall years because of the monthly time step of the model. In July 1998, for instance, extreme rainfall amounts fell in five short (1-2 day) cloudburst events of a very small geographic scale. On July 12, 1998, a rainfall station at Parasi (near the top of the basin) recorded 121 mm of rain in 24 hours. Surrounding stations less than 20 km away recorded only 35 mm in the same time period (NWCF, 2006). As the model relies on the monthly averaged rainfall and monthly averages of the large-scale climate variables, the highly unstable, day to couple of days, atmospheric conditions that generate the localized cloudbursts are not captured in the monthly time step of

the model.

While the model does not represent extreme rainfall events well, it does capture the high range of variability and uncertainty in rainfall in the basin. The ability to capture variability is key in climate predictions. While cloudbursts and extreme rainfall events do cause severe floods in the Rohini Basin, it is the small-degree flooding that occurs every couple of years that contributes to the endemic poverty in the basin. *It is the continued, highly variable, small weather events that slowly erode crops, land and livelihood assets.*

The months of January, September and October proved extremely difficult to model accurately. January is dry in most years. When rainfall does occur in this month, it is due to remnants of depressions from the Mediterranean that transport moisture into Nepal. The timescale of these depressions are on the order of a couple of days,

as well, and are not captured in the monthly time step of the model. During September and October, the atmospheric conditions that allow for the monsoon are decaying and the atmosphere does not reach a stable state until toward the end of the October. The model cannot capture these rapidly changing atmospheric processes.

Thus, over the testing period, the model is better able to replicate rainfall in some months than in others. We can say that we have higher confidence in the model's ability for months in which the model was able to hindcast at the 95th percentile or higher. The 95th percentile means if we were to randomly pick a number, it would have a 1 in 20 chance of being the correct rainfall, which is a pretty low chance. The 90th percentile indicates a 1 in 10 chance of randomly guessing the correct rainfall. If the probability of randomly guessing the correct rainfall is high, it means that the model does not have great skill. Therefore, we can say that we have high confidence in the model's ability in February to May and August, November and December. We have some confidence of the model's ability in June and July, but not great confidence. We have no confidence in January, September or October. This means that we have limited confidence in the climate change projections for June and July and very little confidence in projections for January, September and December. The limited confidence in the monsoon months of June and July are troubling, as a significant portion of the annual rainfall occurs during these months and we would like greater certainty for flood forecasting. However, it does not appear possible to improve the model's performance during these months.

Climate Change Projections

Once we ran the model over the test period of 1976-2006 and were satisfied that the model was performing as well as it could, we pushed the model to make forecasts of possible rainfall futures for the Rohini Basin using different climate change scenarios. As mentioned in the methodology section, the climate change scenarios are introduced into the model by forming the feature vector [F] from the CGCM3 data. As we have ten different climate change possibilities from CGCM3, the model was run ten different times.



FIGURE 5 Boxplots of the projected rainfall under the climate change scenarios A2 (run 1) and B2 (run 1)

The solid red line is the historical (1976-2006) median precipitation value for August. The solid blue line represents the new, climate change projected 50th percentile rainfall value. It is apparent that the new median rainfall values are higher.

There is a great deal of uncertainty in future projections of climate change impacts on the precipitation patterns of the Rohini Basin, as seen in Figure 5. The uncertainty indicates potentially greater variability low-frequency weather events. The uncertainty of the climate change projections is due to a number of factors, which are described in greater detail in Section 6. The boxes in the plots are not narrow and the whiskers (dotted lines) extend beyond the boxes, indicating potentially enhanced variability, particularly in the monsoon months. During the nonmonsoon months, the boxplots are tighter and less variability in rainfall is seen. It is better to utilize the ensemble projections as a range of possible precipitation, and not try to expect a single rainfall value, which no climate model could give. The best way to acquire a sense of how rainfall might change is to compare the median ensemble projection (A2: runs 1-5 and B1: runs 1-5) with the historical mean to figure out, on average, if the month is likely to be wetter or drier than the historical period. See Tables 2 and 3.

	Historic	A2R1	A2R2	A2R3	A2R4	A2R5
January	18.20	8.57	8.00	4.61	7.56	4.98
February	16.01	5.90	5.88	5.80	6.27	6.37
March	20.97	2.88	3.93	2.93	3.66	4.87
April	40.76	3.78	3.93	4.16	4.32	3.93
May	127.09	86.56	81.90	89.09	85.34	152.99
June	366.55	410.21	428.08	428.22	382.15	410.33
July	648.29	568.56	582.46	671.93	575.75	511.56
August	476.05	503.08	502.83	507.86	503.71	503.48
September	321.58	346.54	292.18	356.84	352.87	353.27
October	86.90	36.09	24.24	72.14	27.21	26.74
November	8.38	1.21	5.19	1.28	2.02	1.76
December	19.47	116.61	7.97	6.22	7.17	9.05

 TABLE 2
 The median ensemble projections under the A2 scenario (rainfall in mm)

For the majority of the year, the months are projected to be drier than the period 1976-2006. The monsoon months of JJAS are wetter than the historic period.

	Historic	A2R1	A2R2	A2R3	A2R4	A2R5
January	18.20	5.34	8.12	8.21	6.98	7.04
February	16.01	6.25	5.94	6.30	6.23	1.25
March	20.97	5.21	0.01	6.26	3.17	6.18
April	40.76	4.10	4.05	4.15	3.88	3.87
May	127.09	91.24	72.85	81.95	188.08	76.85
June	366.55	424.27	430.13	389.39	470.72	400.36
July	648.29	569.03	569.19	568.01	604.46	584.48
August	476.05	510.78	510.92	504.58	500.50	504.09
September	321.58	346.99	348.84	364.59	292.65	347.80
October	86.90	21.72	30.57	20.08	23.59	24.02
November	8.38	1.18	1.38	1.46	1.80	1.99
December	19.47	7.41	7.31	8.70	8.28	9.60

TABLE 3 The median ensemble projections under the B1 scenario (rainfall in mm)

For the majority of the year, the months are projected to be drier than the period 1976-2006. The monsoon months of June, August and September are wetter than the historic period. Surprisingly, July is projected to be drier under the B1 scenarios.

For the A2 and B1 scenarios, the Rohini Basin appears to be drying out in all months except for the monsoon months of JJAS. Under the B1 scenario, July is projected to be dryer than the historical record. For the both A2 and B1 scenarios, there is strong agreement amongst all the model runs (i.e. the median ensemble member from A2R1 is very similar to all the other runs of A2). The implication of a wetter monsoon season is the potential for increased flooding. Furthermore, because the model had a tendency to underpredict very high precipitation events during the monsoon, it is likely that these future projections are lower than their potential in the A2 or B1 scenarios. The drying of the other months has potentially negative implications on the agricultural seasons, reducing the ability to plant certain types of crops. A generally drier July under the B1 scenario would negatively affect the crucial nursery stage of paddy crop. We have more confidence that the

dryer conditions projected in non-monsoon months are more accurate than the monsoon month projections, because the model was better able to replicate historical rainfalls in non-monsoon months than in monsoon months. We are fairly confident in the projections for the month of August, though, as the model was able to perform well over the test period (this is likely due to well established, stable atmospheric conditions sustaining the monsoon during August, that are not as well established in other monsoon months). The ensemble spread (the range of rainfall values either replicated or projected) is much smaller in non-monsoon months than in monsoon months, indicating smaller model uncertainty and less variability in rainfall.

As noted earlier, it is the degree of uncertainty and variability in the rainfall projections that is extremely important. While we might say with confidence that during the monsoon month of August, both the A2 and B1 scenarios are projecting an average precipitation increase of 6% from the historical mean, the spread of the ensembles is also critical. Even though the average increase might be 6%, there is large year-to-year variability, which implies the potential for more frequent, low-magnitude flood and drought events in the basin. The ability to predict high magnitude events is difficult with this model. However, the greater variability in small events indicates that effective climate adaptation and disaster risk reduction measures need to account for increased variability.

Summary of Findings

The analog, statistical downscaling methodology presented here provides a robust means of translating large-scale climate change scenarios generated by GCMs to potential scenarios at smaller geographic scales. The accuracy and skill of the downscaled outputs is constrained by the quality and quantity of data available at river-basin scales or the geographic region under consideration. The Nepali datasets for the Rohini Basin were too short to capture the full range of historical climatic variability in the basin. The incompleteness of the data is evident in the uncertainty (variability) evident in the model calibration phase and the inability of the model to replicate precipitation patterns in the months of January, September and October. The model provides some skill in the months of June and July, but not as much skill as the remaining months. During the non-monsoon months, the model has a tendency to slightly overpredict rainfall for small rainfall amount events. In the monsoon months of June-August, the model underpredicts rainfall during years of abnormally high (>70th percentile) rainfall.

The uncertainty from hindcasting historical rainfalls propagates forward into the climate change projections for the basin. For both the A2 and B1 scenarios, the model projects a decrease in precipitation in non-monsoon months. During the monsoon months, a slight increase in precipitation is projected. Given the model's dry (wet) bias in monsoon (non-monsoon) months, these future projections are possibly understated. The model does indicate a high degree of uncertainty in its predictions, telling that precipitation variability is likely to increase.

The model relied on the climate change scenarios A2 and B1 from a single GCM to make precipitation predictions for the basin. No other GCMs out of six possible GCMs were considered due to time constraints and data availability. For completeness, climate change projections from another GCM should be used for comparison.

Concluding Discussion

The statistical downscaling method utilized to project potential impacts of climate change on the rainfall patterns of the Rohini Basin proved to be robust in

replicating historically observed rainfall for the period of 1976-2006. *The ability of the model to replicate rainfall or make projections is determined by three factors: the quality and quantity of the data input in the model, the atmospheric instability caused by the basin's proximity to the Himalayan Range and the changing relationships between monsoon rainfall and large-scale climate patterns such as the El Niño Southern Oscillation (ENSO).* Our model's ability to produce rainfall projections with the accuracy of projections made for models of either the United States or Western Europe is hindered by these three factors, which cannot be overcome.

In an ideal climate modelling situation, such as seen in the developed world, datasets of weather and climate indices (such as rainfall or temperature), are available for fifty years or more. The longer datasets give climatologists greater confidence in their ability to make forecasts because longer records provide better insight into the range of weather events that are possible in an area. The number or weather stations per area and the methodology used to collect data are also very important. For instance, Boulder County, in the state of Colorado in the United States, is roughly half the size of the Rohini Basin and has twenty weather stations in which data has been collected since 1948. The measurements of temperature, rainfall and wind speed, amongst other variables are fully automated and recorded hourly. Moreover, the weather data from the Boulder County stations are easily accessible online for a minimal fee.

The situation is not so fortunate in the Rohini Basin. On the Nepal side, data were only available from five weather stations located primarily on the upper, western edge of the basin. Weather records for points in the middle of the basin do not exist. Given the sometimes highly localized nature of cloudbursts and heavy rainfall events during the monsoon months, we cannot be certain that the geographic distribution of the weather stations for which we do have data are really representative of average rainfall conditions in the basin. The rainfall records only extend back to 1976, which is not a statistically long period for recording if there have already been climate shifts in the basin or for capturing the full range of potential rainfall behaviour. Furthermore, Nepal has been experiencing civil unrest for a number of years. The Nepal Tarai, in which the Rohini Basin is partially located, has experienced significant instability, hindering the ability of the individuals in charge of the weather stations to collect data. The government official (anonymous) who provided the weather data indicated that gaps of daily data had been filled in from memory.

On the Indian side of the Rohini Basin, which encompasses 1,943 km², only two weather stations are/were in existence: one at Nautanwa and another at Gorakhpur Airport. The Nautanwa station collected data only for a brief period in 1978 and at sporadic intervals until 2003. The Gorakhpur Airport weather station began collecting data in 1954, with several decades completely missing. For the period of 1976-2006, nearly 35% of the dataset was missing, rendering it useless for this modelling effort. Furthermore, we procured these datasets from the World Meteorological Organisation (WMO). The price for the Indian government's Nautanwa dataset alone was 50,000 rupees and their version proved to be almost identical to the WMO version. We did not inquire about the price of the Gorakhpur Airport dataset. Thus, we have no idea about the true rainfall distribution in the majority of the area of the basin. The lack of Indian rainfall data is a major gap in the model, as nearly 70% of the land area of the basin lies in India.

The second factor limiting our model is the Rohini Basin's proximity to the Himalayan Range. All climate models, whether numerical or statistical, have difficulty in replicating historical weather patterns for areas near or in the major mountain ranges of the world. Every GCM from which the IPCC compiles climate change projects has difficulty in modelling the physical weather and climate processes over the Himalayan, Rocky Mountain, Alps, and Andean mountain ranges. This is because atmospheric processes are affected by heating, pressure and wind changes around mountain peaks. The Himalayas are the highest mountain range in the world and the area extent of their weather/climate influence is quite large. Indeed, it is not certain that the South Asian Monsoon would exist without the presence of the Himalayas.

The final factor, the changing relationship between monsoon rainfall and large-scale climate predictors such as ENSO or the snow cover over the Tibetan Plateau, hinders confidence in the ability of all climate models to project how climate change will impact the monsoon. For many years, there was a strong relationship between the monsoon and ENSO: during El Niño years the monsoon tended to be weaker and drought was widespread; during La Niña years, the monsoon was stronger. Over the past fifteen to twenty years, however, the relationship between ENSO and the monsoon has been breaking down (Ihara et al., 2006; Kumar et al., 2006; Douville, 2006). Furthermore, none of the GCMs can reliably replicate all the features (sea surface temperature, cloudiness, pressure changes, etc.) of ENSO and all of the projections of ENSO under climate change scenarios are different (de Szoeke and Xie, 2008). Due to the breakdown in the relationship between ENSO and the monsoon, the inability of the GCMs to project ENSO, we did not incorporate ENSO into our downscaling model.

We can say with certainty that the model's ability to project rainfall is severely limited by the data constraints under which we had to operate. The Nepali saying "Ké garné? - What to do?" is particularly apropos. The reality of the weather data available for the Rohini Basin is the same reality in the majority of the developing world. It is in developing nations that individuals are more vulnerable to current climate hazards and likely the most vulnerable to climate change impacts. Without a better sense of potential climate change impacts at smaller geographic scales than 100-200km, it is difficult to begin planning and implementing adaptation or disaster risk reduction measures.

Finally, we have to caution about treating the climate change projections of GCMs as completely certain. The IPCC climate change scenarios were developed by a consortium of scientists after careful analysis of social, economic, and energy use trends. Despite the scientific analysis, the IPCC climate change scenarios are only educated guesses of future energy use and how societies will evolve in the next century. The climate change projections by the GCMs are conditioned on these

23

best-guess climate change scenarios. The lack of certainty in climate change scenarios, coupled with lack of complete understanding about the relationships between various physical land, ocean and atmospheric processes warrants caution in relying upon traditional engineering solutions as adaptation measures. *The lack of certainty in climate change scenarios DOES NOT imply that we should not believe in climate change*. Indeed, the effects of climate change are already beginning to be felt around the world. Some effects, such as the rapid melting of the Arctic and Greenland ice sheets is more profound than that being projected by the GCMs, indicating that climate change processes might be occurring faster and be more severe than we can guess.

References

- Christensen, J.H. et al. (2007), Regional Climate Projections, In: Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change [Solomon, S., D. Qin, M. Manning, Z. Chen, M. Marquis, K.B. Averyt, M. Tignor and H.L. Miller (eds.)], Cambridge University Press: Cambridge, UK.
- De Szoeke, S.P. & S.P. Xie (2008), The Tropical Eastern Pacific Seasonal Cycle: Assessment of Errors and Mechanisms in the IPCC AR4 Coupled Ocean-Atmosphere General Circulation Models, *Journal of Climate 21*, 2573-2590.
- Dibike, Y.B. & P. Coulibaly (2005), Hydrologic impact of climate change in the Saguenay watershed: comparison of downscaling methods and hydrologic models, *Journal of Hydrology 307*, 145-163.
- Dixit, A. (2006), *Reconceptualizing flood mitigation in Tarai*, 168 pp., NWCF: Kathmandu. (Unpublished paper)
- Dixit, A. et al. (2007), Flood Disaster Impacts and Responses in Nepal Tarai's Marginalised Basins, In: *Working with the Winds of Change: Toward Strategies for Responding to the Risks Associated with Climate Change and Other Hazards* [Moench, M. & A. Dixit (eds.)], pp. 119-157, ISET-International: Boulder and ISET-Nepal: Kathmandu.
- Douville, H. (2006), Impact of Regional SST Anomalies on the Indian Monsoon Response to Global Warming in the CNRM Climate Model, *Journal of Climate 19*, 2008-2024.
- Fasullo, J. & P.J. Webster (2003), A Hydrologic Definition of Indian Monsoon Onset and Withdrawal, *Journal of Climate 16*, 3200-3211.
- Gangopadhyay, S., M. Clark & B. Rajagopalan (2005), Statistical downscaling using K-nearest neighbors, *Water Resources Research, 41 W0204.*
- Ihara, C. et al. (2006), Indian Summer Monsoon Rainfall and its Link with ENSO and Indian Ocean Climate Indices, *International Journal of Climatology*, DOI: 10.1002/joc.1394.
- IPCC (2000), *Emission Scenarios*, [Nakicenovic, N. and Stuart, R. (eds.)], 570pp., Cambridge University Press: Cambridge, UK.

- Kalnay, E. et al. (1996), The NCEP/NCAR reanalysis 40-year project, Bulletin of the American Meteorological Society, 77, 437-471.
- Kripalani, R.H., J.H. Oh, A. Kulkarni, S.S. Sabade & H.S. Chaudhari (2007), South Asian summer monsoon precipitation variability: Coupled climate model simulations and projections under IPCC AR4, *Theoretical and Applied Climatology 90*, 133-159.
- Kumar, K.K. et al. (2006), Unravelling the Mystery of Indian Monsoon Failure During El Niño, *Science 90 (12)*, 115-119.
- Littlewood, I.G. et al. (2007), Predicting daily streamflow using rainfall forecasts, a simple loss module and unit hydrographs: Two Brazilian catchments, *Environmental Modelling & Software 22*, 1229-1239.
- Meehl, G.A. & J.M. Arblaster (2002), The Tropospheric Biennial Oscillation and Asian-Australian Monsoon Rainfall, *Journal of Climate 15*, 722-44.
- Moench, M. & A. Dixit (Eds.) (2004), Adaptive Capacity and Livelihood Resilience: Adaptive Strategies for Responding to Floods and Droughts in South Asia, 214pp., ISET-International: Boulder and ISET-Nepal: Kathmandu.
- Opitz-Stapleton, S. & S. Gangopadhyay *(in press)*, Developing Monthly Precipitation Ensembles from Large-scale Climate Fields Using a Non-Parametric Statistical Downscaling Algorithm with an Application to the Rohini River Basin, Nepal, *Journal of Hydrology*.
- Osborn, T.J. et al. (1999), Evaluation of the North Atlantic Oscillation as simulated by a climate model, *Climate Dynamics 15*, 685-702.
- Saji, N.H, S.P. Xie & T. Yamagata (2006), Tropical Indian Ocean Variability in the IPCC Twentieth-Century Climate Simulations, *Journal of Climate 19*, 4397-4417.
- Tolika, K. et al. (2006), An Evaluation of a General Circulation Model (GCM) and the NCEP-NCAR Reanalysis Data for Winter Precipitation in Greece, *International Journal of Climatology 26*, 935-955.
- Torrence, C. & P.J. Webster (1999), Interdecadal Changes in the ENSO-Monsoon System, *Journal of Climate 12*, 2679-2690.
- Trigo, R.M. & J.P. Palutikof (2001), Precipitation Scenarios over Iberia: A Comparison between Direct GCM Output and Different Downscaling Techniques, *Journal of Climate 14*, 4422-4446.
- Venables, W.N. & B.D. Ripley (2002), *Modern Applied Statistics with S* (4th Ed.), 495 pp., Springer: London.

Annex I: Working Paper Series

Paper			
Number WP 1	Title The Cost-Benefit Analysis Methodology	Lead Authors Reinhard Mechler (IIASA)	Focus CBA methods
WP 2	Pinning Down Vulnerability: From Narratives to Numbers	Daanish Mustafa (KCL); Sara Ahmed, Eva Saroch (ISET-India)	VCI methods
WP 3	Downscaling: Potential Climate Change Impacts in the Rohini Basin, Nepal and India	Sarah Opitz-Stapleton (ISET); Subhrendu Gangopadhyay (University of Colorado, Boulder)	Climate downscaling methods
WP 4	Evaluating Costs and Benefits of Flood Reduction Under Changing Climatic Conditions: Case of the Rohini River Basin, India	Daniel Kull (IIASA); Praveen Singh, Shashikant Chopde (WII); Shiraz A. Wajih (GEAG)	India floods
WP 5	Uttar Pradesh Drought Cost-Benefit Analysis, India	Reinhard Mechler, Stefan Hochrainer, Daniel Kull (IIASA); Praveen Singh, Shashikant Chopde (WII); Shiraz A. Wajih (GEAG)	India drought
WP 6	Costs and Benefits of Flood Mitigation in the Lower Bagmati Basin: Case of Nepal Tarai and North Bihar, India	Ajaya Dixit, Anil Pokhrel (ISET- Nepal); Marcus Moench (ISET)	Nepal Tarai and North Bihar floods
WP 7	Pakistan Case Study: Evaluating the Costs and Benefits of Disaster Risk Reduction under Changing Climatic Conditions	Fawad Khan (ISET-Pakistan); Daanish Mustafa (KCL); Daniel Kull (IIASA)	Pakistan (urban) floods
WP 8	Moving from Concepts to Practice: A Process and Methodology Summary for Identifying Effective Avenues for Risk Management Under Changing Climatic Conditions	Marcus Moench (ISET); Sara Ahmed (ISET-India); Reinhard Mechler (IIASA); Daanish Mustafa (KCL); Ajaya Dixit (ISET-Nepal); Sarah Opitz-Stapleton (ISET); Fawad Khan (ISET-Pakistan); Daniel Kull (IIASA)	Methodology summary
WP 9	Understanding the Costs and Benefits of Disaster Risk Reduction under Changing Climatic Conditions	Marcus Moench (ISET)	Summary report

Working

Annex II: Acknowledgements

This paper provides insights from an evaluation of the costs and benefits of disaster risk reduction and adaptation to climate change in South Asia. The report is based on a set of work undertaken in the Nepal Tarai, Eastern Uttar Pradesh, and Rawalpindi, Pakistan. The progamme as a whole is financed by DFID and has been undertaken in conjunction with related activities supported by IDRC, NOAA and ProVention. The support of all these organizations is gratefully acknowledged. Numerous organizations and individuals have contributed in a substantive way to the successful completion of this report. The core group of partners undertaking field work and analysis included: Reinhard Mechler, Daniel Kull, Stefan Hochrainer, Unmesh Patnaik and Joanne Bayer from IIASA in Austria; Sara Ahmed, ISET Associate, Eva Saroch; Shashikant Chopde, Praveen Singh, Sunandan Tiwari, Mamta Borgoyary and Sharmistha Bose of Winrock International India; Ajaya Dixit and Anil Pokhrel from ISET-Nepal; Marcus Moench and Sarah Opitz-Stapleton from ISET; Syed Ayub Qutub from PIEDAR, Pakistan; Shiraz A. Wajih, Abhilash Srivastav and Gyaneshwar Singh of Gorakhpur Environmental Action Group in Gorakhpur, Uttar Pradesh, India; Madhukar Upadhya and Kanchan Mani Dixit from Nepal Water Conservation Foundation in Kathmandu; Daanish Mustafa from King's College London; Fawad Khan, ISET Associate and Atta ur Rehman Sheikh; Subhrendu Gangopadhyay of Environmental Studies Program, University of Colorado, Boulder. Shashikant Chopde and Sonam Bennett-Vasseux from ISET made substantive editorial and other contributions to the project. Substantive inputs from field research were also contributed in India, Nepal and Pakistan by numerous dedicated field staff and individuals in government and nongovernment organizations as well as the local communities that they interacted with.

