# HighNoon Delivery Report

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**To complete by the Coordinator**

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Regional Projections of North Indian Climate for Adaptation Studies

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Abstract

Adaptation is increasingly important for regions around the world where large changes in climate could have an impact on populations and industry. The Brahmaputra - Ganges catchments have a large population, a main industry of agriculture and a growing Hydro-power industry, making the region susceptible to changes in the Indian Summer Monsoon, annually the main water source. The HighNoon project has completed four regional climate model simulations for India and the Himalaya at high resolution (25km) from 1960-2100 to provide an ensemble of simulations for the region. In this paper we have assessed the ensemble for these catchments, comparing the simulations with observations, to give credence that the simulations provide a realistic representation of atmospheric processes and therefore future climate. We have illustrated how these simulations could be used to provide information on potential future climate impacts and therefore aid decision-making using climatology and threshold analysis. The ensemble analysis shows an increase in temperature between the baseline (1970-2000) and the 2050s (2040-2070) of between 2 and 4°C and an increase in the number of days with maximum temperatures above 28°C and 35°C. There is less certainty for precipitation and runoff which show considerable variability, even in this relatively small ensemble, spanning zero. The HighNoon ensemble is the most complete data for the region providing useful information on a wide range of variables for the regional climate of the Brahmaputra – Ganges region, however there are processes not yet included in the models that could have an impact on the simulations of future climate. We have discussed these processes and show that the range from the HighNoon ensemble is similar in magnitude to potential changes in projections where these processes are included. Therefore strategies for adaptation must be robust and flexible allowing for advances in the science and natural environmental changes.
Introduction

Carbon dioxide emissions from anthropogenic sources are now widely considered very likely to have contributed to observed changes in climate (Meehl et al, 2007). The Intergovernmental Panel on Climate Change (IPCC, 2007) also highlight in its fourth assessment report (AR4) that inertia in the climate system, the atmospheric lifetime of Carbon dioxide and feedbacks within the climate system mean that previous emissions will continue to have an impact into the future. We are therefore already committed to some level of climate change at least to the middle of the 21st century which means that adaptation to a changing climate will be a necessity around the world in the next few decades, increasing in priority for more vulnerable populations. Often the change in climate is discussed in terms of global mean temperature, for example Betts et al (2011) focuses on the potential for breaching the threshold of 4°C in global mean temperature. However, regionally, a global mean temperature change can translate to a much bigger or smaller regional or local temperature change; therefore for adaptation purposes, analysis of climate change for individual regions is important.

The EU funded HighNoon project focuses on how water resources may change in the future for the region of South Asia, specifically Northern India; the region comprises the Indian Himalayas and its foothills, home to an estimated 500 million people. The economy is predominantly rural, highly dependant on climate sensitive sectors such as the agricultural and horticultural industry and characterized by a large demand for water resources. In India agricultural use comprises 80 or 90% of human water extraction with almost 60% of this from groundwater. This large demand is part of an increasing trend with groundwater withdrawals increasing by 113-fold between 1950 and 1985 (Douglas et al, 2006). Products using a combination of models with satellite observations (during the period 2002 to 2008) from GRACE (NASA Gravity Recovery and Climate Experiment Satellites) have shown this trend has continued suggesting a mean depletion in groundwater of $4.0 \pm 1.0 \, \text{cm yr}^{-1}$ (Rodell et al, 2009). This increased demand and use of previously unavailable water resource has resulted in a rapid rate of economic development and has helped alleviate poverty in the region. However as a result, groundwater stores have declined at a rate of 20cm per year in as many as 15 Indian states. In most of these states the resource from ground water is projected to dry out as soon as 2025 (Douglas et al, 2006, 2009). On the other hand, most Himalayan glaciers, the largest ice pack outside the poles, have been retreating over the past decades (Bolch
et al., 2011). The relative contribution of snow and glacier melt to river flows decreases with increasing distance from the mountains and may vary from 10% or less annually (Immerzeel, 2010) to 12–38% during the months of March, April and May (MAM), outside the Indian summer monsoon (ISM defined as extending from June to September, JJAS, Goswami and Xavier, 2005) when other sources of water are scarce. This contribution is likely to decrease with increasing glacier wasting (Immerzeel et al., 2010, Siderius et al, submitted). Irrigation and drinking water supplies are thus likely to decrease and become seasonal if water deficits are not compensated for by increased precipitation.

The ISM has been a critical source of water for this region in terms of ground water recharge, river basin and river flow (Rodell et al, 2009) with the HighNoon region (defined by 25°N79°E -32°N88°E and illustrated in Figure 1, centre) receiving up to 70% of its annual precipitation during this period based on APHRODITE data from 1979-2007 (Yatagai et al., 2009). The ISM could become even more important in the future as other sources of water for agriculture and domestic use could become more scarce and inter-sectoral competition for water may increase. Future changes in precipitation amounts and timing could therefore be of critical importance to the region.

Apart from changes in the ISM other fundamental climatic changes impacting Northern India could be many and varied, some examples are given here:

- Increases in temperature could mean certain crops may no longer be viable at lower elevations, while rendering mountain areas at higher elevations suitable for horti-agricultural purposes. Kumar et al (2011b) highlights the potential losses in wheat production with rising temperatures (4–5 million tonnes with every 1°C increase in temperature throughout the growing period with current land use). However, in the case of irrigated rice, the negative impacts of increasing temperature may be adequately compensated by high CO₂ concentrations (Kumar et al, 2011b).

- Sea level rise could lead to salt water intrusion into highly productive deltas rendering large areas of agricultural land no longer tenable potentially causing population displacement (Dasgupta, 2007);

- Altered patterns of snow and glacial melt changing the availability of water for spring and summer irrigation or possibly causing sporadic flooding (Dasgupta, 2007).

- Changes in weather extremes, leading among others to cloud bursts or flash floods could also put additional stresses on critical infrastructure such as roads,
rail and energy supply networks. Such networks are already under stress from population growth, increased urbanization, resource use, and regionally imbalanced economic growth. This could critically impair economic growth by disrupting connectivity or damaging basic service installations such as water supply and drainage (Naswa and Garg, 2011).

Acting to adapt to altered availability of resources and potential changes in extreme weather is therefore an urgent need for this region, especially if the economic growth it has experienced in recent years is to be sustained. In order to adapt a population needs to make informed decisions both in terms of policy and as individuals. In recent years through the publication of the IPCC reports, climate models have become more accessible as tools to aid decisions for adaptation, for example, through methods such as climatology assessments and threshold analysis.

Climatology assessments are important in developing a general understanding of regional climate change using standard climate parameters such as temperature and precipitation. They are often used for presenting key generic messages including uncertainties for policy makers, for example in the IPCC AR4. Threshold analysis, on the other hand, is suited to more specific adaptation applications, such as the rail and power distribution network (Thornton et al., 2011; McColl et al., 2011) making climate information directly useable by, and relevant for, specific industries.

Many industries (See Table I), for example agriculture, are influenced directly by weather and climate on a wide range of timescales (e.g. precipitation, temperature and CO₂ concentrations) and indirectly (e.g. by changes in the occurrence of pests and diseases, or changing market forces). Adaptation in the agricultural industry tends to be influenced by knowledge of the local climate and individual experience (Gornall et al, 2010). Changes to the local climate could threaten established farming methods; however adaptation to climate change could provide the mechanism through which these methods could be improved. Hydroelectric power is another important industry in India with the Brahmaputra catchment and Ganges highlighted by the World Development Bank as key areas with potential for development (Ramanathan and Abeygunawardena, 2007). The benefits and problems from such developments need to be evaluated using understanding of the likely future changes to precipitation and runoff in order to ensure facilities are developed in a robust and resilient way.
The use of scientific information in policy making is often complicated due to the uncertainties inherent in the climate system, which in reality can never be entirely eliminated (Webster, 2003), and those due to scientific understanding, which has seen rapid development in recent years. One of the overarching issues is uncertainty in the size and, for some regions, direction of future projected changes in water-related quantities. For example, the IPCC AR4 climate models do not agree on the sign of annual/seasonal precipitation changes for some key regions, including South Asia - particularly for December January February (DJF). In other regions and seasons there may be greater consensus on the sign of future changes, but a wide range of magnitudes may be projected across the models. These uncertainties are potentially challenging for assessing the scale and nature of adaptation options required.

In this paper we describe the latest high-resolution (25km) ensemble of regional climate model (RCM) simulations run for the HighNoon project for India and the Himalayas. These simulations covering the whole of India (See Figure 1, centre) are described and evaluated in detail in Pankaj et al (in preparation). We briefly verify model performance in simulating the current climate of the specific region of the Ganges and Brahmaputra catchments (Section 0). This is then extended to assess the use of the ensemble to provide information on climate change impacts on adaptation timescales (i.e. to the middle of the 21st century; IPCC, 2007), providing information for adaptation decisions for these catchments using the methods described above (climatology assessment and threshold analysis, Section 0). We also discuss the main sources of uncertainty and the potential limitations of these model simulations (Section 0).

HighNoon simulations

Experiment design

The HighNoon regional climate model simulations provide data at a 25km resolution for the HighNoon domain (See [Figure 1, centre]) for the period the 1960 to 2100 using the SRES A1B scenario (Nakićenović et al. 2000). Two global models that represent the monsoon well for the current climate; The Third Version of the Met Office Hadley Centre Climate Model (HadCM3; Pope et al. 2000, Gordon et al, 2000 – A version of the Met Office Unified Model, MetUM) and ECHAM5 (3rd realization, Roeckner.et al, 2003) provide the boundary conditions for the two regional climate models; REMO (Jacob, 2001, 2009) and HadRM3 (Jones, 2004). This is illustrated by the flow chart shown in
Figure 2, which shows the inputs, the main processes and outputs of a typical RCM. The configuration of HadRM3 includes representation of land surface sub-gridscale heterogeneity provided by version 2.2 of the Met Office Surface Exchange Scheme (MOSES 2, Essery et al., 2003). The combination of two RCMs each driven by two GCMs provides an ensemble of four high resolution model simulations for the HighNoon domain (See Figure 1).

The influence of horizontal resolution on the simulations is illustrated in Figure 1 which shows three plots of June precipitation climatologies; a global-scale HadCM3 simulation (left), a regional-scale 25km resolution HadRM3 simulation (centre), the latter driven with HadCM3 data at the boundaries and APHRODITE observations (right). Figure 1 (left) shows clearly visible gridcells with limited detail around the coastlines, over orography or the Indo-Gangetic plains. In contrast, the 25km RCM is more detailed with the coastlines and other features represented in more detail. Comparing the observed June APHRODITE climatology (Figure 1, right) with the RCM illustrates the improvements in the representation of current climate by using high resolution RCM simulations.

Assessment of HighNoon simulations

Future climate projections may be treated with more credibility if a given model can realistically simulate the physical and dynamical processes of the current climate since it may adequately capture the fundamental processes and therefore project a plausible future climate (Liang et al, 2008). In this section the outputs from the HighNoon ensemble are compared with observations to verify that the simulations capture the main features of the current climate of the Ganges Brahmaputra region in order to provide confidence in the analysis of the future period of 2040-2070 presented in Section 0.

Figure 3 shows the annual cycle of 30-year climatologies, for the Ganges and Brahmaputra catchment (highlighted by the black outline in Figure 4) using the baseline period 1970-2000 of temperature (top row) and precipitation (bottom row) for both global (left column) and the regional 25km data (right column). The shaded region represents 2-standard deviations in the 30-year means of a 150-year control global HadCM3 run. Natural climate variability is commonly represented by ±two standard deviations of a long control climate model simulation (Collins et al. 2001; Cowling et al. 2009). Hence
changes outside this range may be considered as a signal outside the “noise” of natural climate variability. Excluding changes within ± two standard deviations of the control simulation is approximately equivalent to a signal:noise ratio of 2 (Hawkins & Sutton, 2010). The global models show a larger annual cycle of temperature than that shown in the global observation dataset (CRU temperatures: Mitchell and Jones, 2005). The ensemble of regional model simulations has an improved range although one model (ECHAM5-REMO) shows a shift in phase of the annual cycle – earlier by one month; this could be associated with the way that the REMO land-surface soil properties are specified see Section 0 for discussion of the REMO soil properties used in the HighNoon ensemble.

The annual cycle of precipitation (Figure 3, bottom row) shows that there is more variability in simulations of precipitation than temperature, with HadCM3 having a strong annual cycle and ERA-Interim (Simmons et al, 2007, 2010) a weak cycle compared to observations (CMAP Precipitation, Xie and Arkin, 1997). The global models (Figure 3, bottom left) diverge during JJAS tending to underestimate the rainfall during this period compared to observations. The regional models (Figure 3, bottom right) generally compare well against the APHRODITE observations, but have longer wet seasons such that they overestimate the observed precipitation between January and June. This difference between the model and observations should not be over-interpreted as the large spread in the precipitation observations mean it is difficult to robustly attach error bars to the observations for this region, particularly given the relative scarcity of observations in the mountains (this is also illustrated in Figure 6a).

[Figure 3]

The spatial pattern of the observed and model temperature and precipitation climatologies are shown in Figure 4 and Figure 5 respectively for the wet season (JJAS). The temperature observations shown in Figure 4 (top row, left) are CRU observations and are therefore lower resolution than the regional models. This considered the model climatologies all show a reasonable approximation to the observed climatology; a more in depth analysis of the models for the whole HighNoon domain is completed in Pankaj et al (in preparation). Figure 5 shows three observed precipitation climatologies (first row), of these APHRODITE (Figure 5, first row, centre) is the highest resolution and shows the region of highest rainfall along the Himalayan foothills, although observations are sparse in this region. The regional model climatologies show the region of maximum rainfall to
be slightly further north. In other seasons there is a general over estimation in the models of the precipitation in the east of the catchments, particularly in the pre-monsoon season (MAM – not shown).

[Figure 4]

[Figure 5]

Figure 6 shows a comparison of the observed; GPCP (Adler et al, 2003), CRU, GPCC (Beck et al, 2005, Rudolf and Schneider, 2005, Rudolf et al, 2005), and APHRODITE JJAS precipitation, averaged across the HighNoon domain, with two regional simulations which use ERA-Interim global re-analysis data to provide boundary conditions. Figure 6a shows a decreasing trend in the observations (except APHRODITE), and for the ERA-Interim forced models; HadRM3 shows a trend of increasing precipitation while REMO shows no trend but strong decadal variability. There is some agreement across the observational datasets on seasonal precipitation extremes; the models show a range of interannual variability (IAV) in agreement with the APHRODITE data. The correlation of the IAV from APHRODITE and the RCMs, shown in Figure 6b, is 0.42 for REMO and 0.38 for HadRM3. Such low correlations may be related to the weak annual cycle in the ERA-Interim precipitation, (Figure 3) the model representation of convection (Pal, 2007), and the model ability to recycle precipitation through evaporation (Giorgi and Bi 2000).

[Figure 6]

Though the number of models in the HighNoon ensemble is limited and therefore spread in the HighNoon ensemble is relatively small, in general, the models do represent the current climate in terms of the seasonality of temperature and precipitation, and therefore provide useful information about the Brahmaputtra and Ganges region. This is reflected in the analysis presented in Pankaj et al (in preparation) which analyses the RCM ensemble (using ERA-Interim boundary conditions) for the whole of India. The model simulations capture the major rainfall regimes over India compared to observations (Indian Meteorological Department, IMD). The temperature patterns are also well simulated though they showed a schematic cold bias for country as a whole, also reported in IPCC 2007.
Climate projections in adaptation studies

The assessment of the ensemble members (Section 0) demonstrates that the models in the HighNoon ensemble simulate the important processes of the current climate and therefore should simulate a realistic future climate for the Ganges and Brahmaputra regions (Liang et al, 2008). The climate projections provide information on a range of timescales, however at very short timescales the natural variability masks the climate signal and therefore we use 30-year means to analyse future changes in climate.

In this section we explore how the output from RCMs can be used directly in studies of adaptation focussing on the 30-year period centred on the 2050s (2040-2070) as this timescale is appropriate to inform adaptation policies (IPCC, 2007). This is mainly due to the inertia in the climate system which means that some change in climate is inevitable, and will be evident by the 2050s given the emissions already in the atmosphere (IPCC, 2007).

Using the climate projections

The analysis of the HighNoon RCM ensembles presented here suggests two possible approaches for general analysis; the first considers the 30-year seasonal means and the differences between the projection of the future period (here the 2040-2070) and the estimate of the current climate provided by the period 1970-2000 (Section 0 applies this method to the HighNoon ensemble); this is a more generic method which is independent of the end user or the application. The second approach uses known thresholds at which a climate variable is known to have an impact, for example, if the temperature exceeds 35°C during the critical flowering period of a rice crop it can cause infertility of the plant (Yoshida, 1981) and therefore detrimentally impact the crop yield (Section 0 applies this method to members of the HighNoon ensemble). This requires some knowledge of the end user as this information is more specific; however thresholds of standard parameters such as temperature and precipitation could have multiple applications.

Climatology analysis

The HighNoon ensemble analysis focuses on the Ganges and Brahmaputra catchments for two 30-year periods; the baseline (1970-2000) and future (2040-2070) and three variables; temperature, precipitation and runoff. Figure 7 (left column) shows the annual cycle for the temperature, precipitation and runoff across the four member HighNoon ensemble for these two periods. The magnitude of the differences between the two
periods is shown in Figure 7 (right column). Figure 7 (top row) shows that there is a near constant increase in the regional mean temperature across the four ensemble members by the 2050s, in the annual mean of between 2.5 and 3°C. These values compare with the projections of the 23 member AR4 ensemble which shows an annual mean temperature rise of $2 \pm 1^\circ$C (Kumar et al., 2011a). Thus, the RCM ensemble under-samples the uncertainty, with projections at the higher range indicated by the AR4 global models. Across the annual cycle, the RCMs show temperature changes of between 2 and 4°C, with suggestions that the mean dry season temperature (DJF) could increase more than the mean JJAS temperature.

The spatial distributions of the temperature changes (not shown) are similar across the catchment although during DJF and SON the temperature rise is greatest in the mountainous regions of the catchment. An increase in temperature at higher elevations could have impacts on the glacial melt and the risk of glacial lake related floods, possibly making runoff from glacial melt and snowmelt occur earlier in the year. Increases in temperature could also mean that regions previously too cold for crops become more temperate therefore increasing the viability of land at higher elevations for horticultural activities. At lower elevations where temperatures are already at the physiological maxima for crops, the impact of even a small increase in temperature could be detrimental to crop yields (Gornall et al 2010). In order to adapt to increasing temperatures, a shift in the growing season to avoid the highest temperatures might be necessary which could itself have an additional impact on the regional climate by altering irrigation demands (see Section 0).

[Figure 7]

There is considerable uncertainty within the ensemble with regard to changes in wet season precipitation illustrated in Figure 7 (middle row). Precipitation also has a much more variable spatial distribution. These are highlighted in Figure 8, which shows the difference between 2040-2070 and 1970-2000 climatologies of total precipitation for JJAS for the Ganges Brahmaputra catchment (highlighted with the black outline) for the HighNoon ensemble. March, April and May (MAM, not shown) also showed distinct spatial differences, in particular, there was an increase in all four ensemble members to the East of the catchment and a reduction in the west.

The annual cycle in runoff is shown for those members of the HighNoon ensemble for which data were available, Figure 7 (bottom row). In general the two HadRM3
simulations show an increase in the runoff through most of the year, with the REMO run driven by ECHAM5 showing a slight reduction during certain months of the year (e.g. April, August November and December). The spatial distribution is not uniform across the catchment; this is illustrated in the difference (2040-2070 minus 1970-2000) plots of runoff shown Figure 9.

In both precipitation and runoff the ensemble members span zero and therefore even given the similarities between these models, there are considerable differences in their projections of future climate. This highlights that projections of rainfall and runoff are more variable and therefore less certain than those for temperature, where all the models in this analysis agree on sign if not magnitude. This is highlighted in the summary table given in Table II. The uncertainty in precipitation is supported in the AR4 model ensemble which indicates a small, 5%, increase in monsoon season rainfall (by 2050), but with an uncertainty of 20% (Kumar et al., 2011a). The variability in runoff and precipitation both in terms of sign of change and spatial pattern means that adaptation strategies should be both robust and flexible (e.g. Hay, 2007; Hertzler, 2007). In addition advances in modelling to include important aspects of the local environment such as, aerosols and their transport, irrigation and land use change may alter the projections presented here (See Sections 0 and 0). Adaptation strategies such as improving the efficiency of water storage and infrastructure are positive changes in any climate. For example, in 2006 Singapore aimed to meet 15% of its water needs using reclaimed wastewater, a process with a low energy requirement (Tortajada, 2006), however Singapore’s national water agency indicate that reclaimed water now accounts for 30% of the nations water needs (PUB, Singapore's national water agency, 2011).

[Table II]

[Figure 8]

[Figure 9]

**Threshold analysis**

The understanding of the vulnerability of a population, sector or industry to current weather and climate is an essential precursor to being able to adapt to potential changes to the climate in the future. Often this understanding is through critical thresholds above which there are impacts on a population or industry, for example, a total monthly rainfall value which could affect infrastructure or a temperature which is significantly warmer
than the average temperature and could therefore cause health problems or crops to fail (see Table I).

The main industry in the Brahmaputra – Ganges catchment is agriculture and in this industry there are many fundamental thresholds that are important. One example of a critical temperature for rice production is a temperature of greater than 35°C during the crucial flowering period as this can affect the fertility of the plant (Yoshida, 1981). Figure 10 (bottom row) shows the change in the number of days per year with the maximum temperature above 35°C between the baseline (1970-2000) and the future (2040-2070) for two of the HighNoon ensembles. In these two ensembles, there is an increase in the number of days exceeding the 35°C threshold across the south of the catchments for these two ensembles of 26 to 28 days on average but an increase of 70 days in the East of the region. On the basis that this region is one suitable in the current climate for multiple crops per year, an increased incidence of periods with temperatures above the 35°C threshold could increase the likelihood of these temperatures coinciding with crops flowering. Further analysis would be necessary on temperature, water availability and other interactions for example the influence of rising CO₂ to diagnose the full regional impact on crop yield.

Another factor important to India is population health and energy demand. Anecdotally a temperature threshold of 28°C has been used (gathered from various online sources, see Section 6.1 for web references 1, 2 and 3) to represent a threshold at which energy demand increases; due to the population using energy to operate cooling mechanisms such as air conditioning to remain comfortable. Sherwood and Huber (2010) also highlight the importance of humidity and how this exacerbates the effect of high temperatures, while the UK Heat Health watch² recognises the importance of cooler nights which allow a period of recovery. Figure 10 (top row) shows the difference between the two periods: 2040-2070s and the baseline (1970-2000) in the mean number of days per year that are projected by these two ensembles to exceed 28°C. Both ensembles indicate an increase in the south of the Ganges-Brahmaputra catchment, with a mean increase of 25 to 30 days for these two ensembles, with a maximum of 80 days in the East of the region.

This large range in the difference between the numbers of days with a maximum temperature that exceeds particular thresholds for the 2050s compared to the baseline is
due to the complex terrain of the region which varies from high mountainous regions to low-lying deltas. Analysis of lower thresholds would be more appropriate for regions of high elevation where the mean temperature is lower; in addition, different temperature thresholds for both health and energy demand may apply to different locations since local infrastructure and local populations may differ in their current adaptation to heat.

**Discussion: Uncertainty and Adaptation**

The model simulations from the HighNoon project are the most complete set of data available for South Asia and are therefore a useful and important resource for the types of climate analyses illustrated in Section 0. However there are uncertainties in the models and understanding of atmospheric processes at both global and regional scales, the implications of which are not yet fully understood and yet could significantly change the regional projections if included in climate models. In this section we describe sources of potential uncertainty in climate models and specific processes that could be particularly relevant for the South Asia region. This uncertainty needs to be accounted for if adaptation related decision making is to be robust.

**Sources of uncertainty**

Climate models are a physical representation of a highly complex system based on mathematical equations that simplify complicated physical processes. In defining a climate the complex system is the whole Earth system, including oceans, atmospheric processes, the land surface and ecosystems and atmospheric chemistry. While parts of this system can be well represented by mathematical relationships, models cannot provide a 'perfect' representation, due to limitations in scientific understanding of the large number of different processes, dependencies and feedbacks and due to limitations in computing resources. Climate models and their projections are therefore affected by many aspects such as the choice of numerical method to solve the dynamical equations; the processes that are included and the parameterizations that are used; as well as any assumptions that are made. All of these potential differences between models mean that every climate model could produce different projections creating a spread of results; this is known as structural uncertainty (Sexton et al, 2011). In addition to uncertainty from the structure and composition of the model, different settings of key parameters within the parameterizations of one model can also lead to a spread in projection results; this is parametric uncertainty (Sexton et al, 2011). For example an uncertain physical parameter relevant to water and agriculture is the relationship between carbon dioxide
concentration in the atmosphere and plant stomatal closure, in this example the uncertainty has considerable implications for water resources (Wiltshire et al., Submitted).

Model and parametric uncertainties are mainly due to the limitations of the current modelling system; however there are other sources of uncertainty that are related more with the chaotic nature of the natural environment; this is referred to as natural internal variability. This type of variability in the climate system occurs from regional scales to large-scale interactions between the atmosphere and oceans such as the El Niño/La Niña-Southern Oscillation (ENSO). Natural external variability includes factors that can influence the climate but are not part of the climate system, such as volcanoes and the solar cycle. Currently, there is no way of predicting how the solar radiation reaching the Earth will change in the future; therefore this is not included in models. There is also no way of predicting when, on climate timescales, a volcano might erupt in the future nor how much ash it will emit into the atmosphere, therefore this is not modelled in any climate projections. Though both of these types of variability are missing in the climate models used in the analysis in this paper, on the 30-year timescales (used Section 0) their effects are considered unlikely to have a large long-term impact.

The third major uncertainty in climate projections is associated with how human activities will influence and interact with the environment. This is dependent on many factors across a broad spectrum from economic and policy driven aspects to social behaviour; making it difficult to predict how the population could change or how future populations might consume resources. In the IPCC AR4, the Special Report on Emissions Scenarios (SRES) representative pathways were used to depict a range of plausible future emissions (Nakićenović et al., 2000); however none of these scenarios represent a mitigation scenario and therefore no projection of the impact of future mitigation is currently available. These scenarios often include assumptions about future changes in population, land use and other socio-economic factors.

The relative roles of these different sources of uncertainty depend on the time scales under consideration. On decadal timescales, the climate change signal is small compared to natural variability, such that uncertainty caused by initial conditions and natural forcing dominates (Hawkins and Sutton, 2009, 2011). This timescale is often consistent with the timescales of adaptation of infrastructure. Research on decadal climate predictions is just emerging (e.g., Collins et al., 2006; Smith et al., 2007;
Keenlyside et al., 2008), and no regional climate predictions on decadal scales currently exist. However, decadal and seasonal prediction may significantly improve our understanding of adaptation requirements over the next few decades (Betts et al., 2009).

The HighNoon RCM ensemble is comprised of four simulations and therefore it is unlikely to capture the full range of uncertainty of a larger ensemble for example, from the IPCC AR4 (IPCC, 2007). The IPCC AR4 ensemble showed a global mean annual temperature change of between 1.7 and 4.4°C for the A1B scenario, regionally for South Asia the change was between 2 and 5°C. Precipitation for South Asia is much more variable in the IPCC ensemble, showing changes in annual precipitation of between -15 and +20% for the A1B scenario. Though the analysis showed here does show a similar range in temperatures and large variation in precipitation, similar to the AR4 ensemble, this analysis is for a much smaller area (just the Ganges-Brahmaputra catchments) than the IPCC South Asia region so the two are not directly comparable.

In general the implications of using an ensemble of future climate projections that captures the uncertainty in the climate system sufficiently may include the following:

- **Strong agreement on sign and magnitude of changes**: more confident adaptation decisions can be made (for example, on both the need to increase water storage, and on the range of capacity required).

- **Agreement on the sign, but not magnitude of changes**: adaptation decisions will need to be more flexible (for example, a broader range of water storage capacity).

- **Disagreement on the sign of changes**: adaptation plans may need to be flexible to changes in both directions (for example, a very broad range of water storage capacity or hedging by planting mixes of different crop types).

**Large scale processes**

Global model simulations supply the large scale information at the boundaries of the RCMs and the correct representation of key large-scale processes is therefore extremely important in constraining the RCMs (Lucas-Picher, 2011). An RCM is first-order sensitive to the driving lateral boundary conditions (Liang et al, 2008) and therefore reduction of the errors in the large-scale circulation will mainly be possible through development of the driving GCM. Therefore it is important to improve representation of physical
processes at the global scale as these could have an impact on regional models, for example ensuring the large scale correlations between flows at remote locations; referred to as teleconnections (James, 1994) are represented properly. The El-Niño Southern Oscillation (ENSO) is a well known teleconnection pattern which is considered to contribute to the total interannual variance over much of the globe (James, 1994). This is particularly important for this region as the interaction between ENSO and the interannual and inter-decadal Hadley circulation has been shown to significantly affect the South Asian Monsoon (Krishnamurthy and Goswami, 2000).

The ISM is a key driver of the climate in South Asia providing the main source of water for populations in India, Bangladesh, Myanmar and Nepal. Therefore understanding the processes, global or more localized, that feedback and affect the intensity of the monsoon rains is important for representing the climate of the region. The RCMs resolve other processes that are important for the regional climate but occur on a resolution too small for global models to resolve such as precipitation enhanced by local orography, coastlines or the effect of land use. Gaining a better understanding of these processes occurring on a regional scale should improve the model representation of the regional climate system and ultimately could affect the range of uncertainty in model projections of future climate.

**Local influences on regional climate**

As previously discussed, the inertia in the global climate is sensitive, partly to the long-lived nature of atmospheric carbon dioxide. Therefore even if atmospheric concentrations are stabilised then the globe will continue to warm indicating a commitment to adaptation. However, on the regional scale, local influences can play a substantial role in the local climate on comparatively shorter timescales. For instance the atmospheric lifetime of black carbon is approximately 1 week. Similarly, irrigation has been shown to alter the climate of South Asia. In the remainder of this section we consider the processes that are not currently represented in the regional model simulations presented here, but could be important; such as black carbon and the occurrence of Atmospheric Brown Clouds, land use, irrigation and soil properties. In some cases these localized processes could substantially alter the climate over the next few decades significantly altering the needs of adaptation.
Atmospheric brown clouds and black carbon

Asia is a region that relies on coal powered energy generation and therefore emissions of black carbon are relatively high in this region, such that UNEP have identified this region as an Atmospheric Brown Clouds (ABC) hotspot. ABCs are regional scale plumes of air pollution consisting of particles (referred to as primary aerosols), black carbon and pollutant gases such as nitrogen oxides (NO\textsubscript{x}), carbon monoxide (CO), sulphur dioxide (SO\textsubscript{2}), ammonia (NH\textsubscript{3}) and other organic gases and acids. ABCs have been shown to have significant impacts on the regional climate of India especially the monsoon (Meehl et al, 2008, Wang et al, 2009); such is the concern over ABCs that a comprehensive impact assessment report on ABCs with particular focus on Asia was commissioned by the United nations Environment Programme (UNEP,2008).

Black carbon particles are typically small in size and chemically inert and therefore remain in the atmosphere for up to a week before they are precipitated or deposited out. This relatively long lifetime in the atmosphere means that these particles can be transported considerable distances away from the emission source and therefore the effects of black carbon can extend well beyond the regions where the concentration is highest. (Wang et al, 2007). Black carbon causes radiation to be absorbed higher in the atmosphere therefore preventing radiation from reaching the surface, simultaneously warming the troposphere and cooling the surface thereby making the atmosphere more stable. The combined effect of this change in distribution of energy through the troposphere and the reduced evaporation from a cooler surface suppresses convective precipitation (Ramanathan, 2005, 2007a, 2007b). Black carbon also absorbs radiation reflected from the surface, hence reducing the amount of radiation that is reflected back into space, thus reinforcing its positive radiative forcing effects.

Black carbon could also affect the lifetime of clouds in the atmosphere and therefore have an impact on large-scale precipitation patterns. The varied composition of ABCs is likely to mean that their effect on precipitation and radiative forcing is likely to vary considerably from region to region. This will mean some areas experiencing increases and others decreases in precipitation. The deposition of black carbon has also been shown to affect snowmelt and glacial melt by reducing its albedo (Qui, 2010). The effects of black carbon and ABCs on the atmosphere are therefore complex and diverse making them difficult to represent fully in climate models. However given that black carbon emissions have increased by three times in South Asia between 1950 and 2000 together
with an observed decrease in ISM precipitation of approximately 5-7% for the same period, ABCs are an increasingly important feature of the Asian climate. In the HighNoon simulations there is no representation of the aerosol species in ABCs or their transport; however it is possible that their impact on future projections could be large and have a significant impact on surface energy and moisture fluxes.

**Land use and Irrigation**

As the population of India grows, demand for food and water could potentially drive changes in land use either to increase the amount of agricultural land or increase the productivity of the land already being farmed. Land use change has been identified as a key driver of climate change not only through absorption or emission of greenhouse gases but also by modifying the physical properties of the land surface (Betts et al, 2006). For example changing the land cover from dark forest to agriculture will mean more exposed bare soils which will affect the surface roughness and albedo as well as the fluxes of moisture and heat (Betts and Ball, 1997). The effects of changes in land use depend on the region and the conditions at a particular location.

There is growing evidence that human activities that change the land surface can have an impact on regional climate. Irrigation is an important modification to the land-surface, essential for the success of agriculture in dry climates such as the Ganges Brahmaputra region. Irrigation has important effects on the hydrological cycle at a number of different stages. Extraction of water from rivers and ground water for irrigation reduces their flow, transferring moisture to the soils and plants, thus modifying the land-surface moisture fluxes through evaporation and transpiration. The changes in vegetation distributions and the increased water vapour present in the atmosphere affects the heat and moisture fluxes at the surface, in turn this has an affect on the generation and lifetime of clouds, which affects precipitation. An example of this is given by Lohar and Pal (1995), they report a reduction in mean monthly rainfall over West Bengal (for example the March rainfall reduced from 50-80mm between 1973 -1982 to 20-40mm between 1983 -1992); a region which has experienced a rapid expansion of summer paddy crop agriculture along the coast (with an increase of more than 3-fold between 1980 and 1990). The high moisture content of paddy fields has reduced the temperature difference between the sea and land, thus reducing the strength of the sea breeze and therefore convection. Douglas et al (2009) show that the effect of moving to irrigated croplands varies regionally but for the Ganges-Brahmaputra basins there is a reduction in the rainfall of between 20-60mm for a 5-day period during the ISM. Douglas et al (2009) demonstrated
that by modifying the moisture flux over a large enough area and reducing the Convective Available Potential Energy (CAPE) the mesoscale convection patterns are modified therefore affecting the rainfall patterns across India. Douglas et al (2006) reported regional differences in latent heat flux across India; with increases in the northern regions due to changes in land-use from drier soils to irrigated agriculture. These reductions in precipitation will have direct consequences on the regeneration of groundwater and the flow of the rivers in the region.

Saeed et al (2009) demonstrate the impact of including an irrigation scheme in an RCM on the modelled South Asian Monsoon using the REMO RCM driven by ERA-40 data (Uppala et al, 2005). In parts of India such as the Indus and Ganges basins, which are highly irrigated regions, there is a warm bias in the model which can be as much as 5°C. Including irrigation in the REMO model reduces the warm bias in the model which weakens the westerly winds from the Arabian Sea. This allows the advection of moist air into western India and Pakistan removing the low precipitation bias also in evidence in these regions. Irrigation also improves the evapotranspiration in these regions by routing water more effectively.

In the RCM runs for HighNoon there is no accounting for the effect of land use change or irrigation and therefore their impact on the regional climate is not captured. Though it is possible to use offline land-surface simulations to route the rivers more effectively this would not capture the feedbacks of the more efficient routing and improve the evapotranspiration on larger scales. Representing physical processes important in the vicinity of steep orography, leading to enhanced ascent of air, affecting cloud and precipitation formation resulting in increased moisture along the upslope (Yasunari 1976; Singh et al. 1995) are likely to improve the precipitation simulations for the region. Also, the important mountainous physical processes such as snow drift/accumulation, liquid to solid precipitation formation, rain shadow effect need explicit driving mechanisms in the model physics (Leung and Ghan 1995). Incorporation of such physical processes will enhance the model reliability towards adaptation issues associated with extremes of precipitation issues such as changing agriculture patterns, population migration and health.

Soil properties

The important influence of soil properties on the climate, particularly the coupling between soil moisture and rainfall have been identified by a number of studies (Kendon
et al 2010, Koster et al, 2004, 2006). Koster et al (2006) identify South Asia as a region with particularly strong coupling which results in a warm bias in models over the region; this is referred to as a hotspot. Though this regime has been identified in several models, a sensitivity study for Europe (Anders and Rockel, 2009) demonstrated that this warm bias is affected by soil type.

In order to isolate the effect of different soil properties two simulations using the 25km REMO RCM using ERA-Interim boundary data for the HighNoon domain were performed; one using the standard soil hydrology and soil thermal characteristic (baseline) and the other using a modified soil thermal characteristic (test). Initial analysis of these simulations suggests that soil properties could be important.

REMO uses the Dümenil and Todini (1992) soil hydrology scheme which uses a bucket type soil module, where each grid-box is represented by a single soil water reservoir i.e. the depth of the bucket. Therefore the water available for evaporation is defined by the rooting depth of the plants and the soil texture properties. The comparison of the current climate from the baseline simulation with CRU observation data sets indicates a warm bias in the surface temperature of as large as 8ºC in some parts of northern regions. In REMO, thermal diffusivity and capacity are parameterized as a function of soil moisture, using external constants as reference values independent of soil moisture. These reference values represent values of a medium moist soil for a mid-latitude rainy climate; however the climate over South Asia is mainly dry categorized as arid or semi-arid climate. Thus in the test simulation the soil thermal characteristic is modified to be more representative of dry soil by changing the thermal diffusivity and the conductivity (Gordon, 2002). The comparison of the test simulation with CRU observation data sets show a reduction of the warm bias observed in the baseline simulation of between 1.5 and 4 ºC.

Summary of missing processes

The list of processes presented here, though not exhaustive, illustrates the considerable uncertainty that arises from these missing processes in the model simulations. For instance, the inclusion of Irrigation can reduce the simulated temperature biases by approximately the same magnitude as the range presented by the ensemble members. Black carbon and other Aerosols in the atmosphere, both in terms of their chemistry and transport, have been observed to have an increasing effect on the regional climate acting
to reduce precipitation during the ISM, however these observed precipitation changes are currently within the range of uncertainty of the HighNoon ensemble.

Conclusions

We have completed four simulations for the HighNoon project covering India and the Himalaya using two different regional models (REMO and HadRM3) with boundary data supplied from two global models (ECHAM5 and HadCM3). Analysis of the ensemble members has shown that they represent the general processes and climate of the region although the observed patterns in rainfall and temperature are not replicated exactly. This ensemble is the most complete (1960-2100) high resolution (25km) data set available for the region providing data across a wide range of model variables. This ensemble provides useful information on the potential future changes in temperature (e.g. increasing mean temperatures of between 2 and 4°C) and precipitation (though precipitation is more variable with a range of ±1mm/day across the ensemble). Analysis of the model data using known critical thresholds can provide useful information for industry, population and infrastructure; for example the change (between 1970-2000 and 2040-2070) in the number of days with maximum temperatures exceeding 28°C is between 25 and 30 days. In using this information it is therefore important to balance the risks versus benefits of the adaptation policy, for example what are the costs of adaptation against the costs of no action, while considering the potential cost of adaptation in response to incomplete science. In this situation there is a requirement for adaptation pathways that do not restrict the future ability to adapt and are therefore resilient to both future advances in science and natural changes in the environment. Therefore the projections discussed here should be viewed as providing scoping information rather than supporting detailed adaptation plans. Regional climate impacts are often strongly dependent on the climate data and scenarios used and the assumptions made, suggesting the need for application of a wider set of common scenarios (including both climate and socio-economic factors), and a more in-depth assessment of assumptions and factors considered to enable a better comparison across studies. This also supports the need for a risk-based approach which considers model skill, confidence, and uncertainties in future projections more comprehensively. In light of the many sources of potential uncertainty discussed above, Hay (2007) and Hertzler (2007) suggest that the development of robust ways of applying uncertain climate information to agricultural decision making (e.g. hedging, foreclosing options, creating new options and diversification) will be critical in planning resilient future
land/water management options for agriculture. Similar approaches will also be important for adaptation planning for other impacts sectors.

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<table>
<thead>
<tr>
<th>Sector</th>
<th>Climate variables</th>
<th>Timescales known to be important for sector</th>
<th>Examples of important thresholds</th>
</tr>
</thead>
<tbody>
<tr>
<td>Agriculture</td>
<td>Temperature</td>
<td><strong>Annual</strong> - important for established farming practises</td>
<td>Max temperature during rice flowering affecting crop yield &gt; 35°C</td>
</tr>
<tr>
<td></td>
<td></td>
<td><strong>Seasonal</strong> - high growing season temperatures can affect crop productivity by bringing forward harvest times. Even high temperatures for only a short period can have severe detrimental effects to some crops if they occur at crucial times e.g. flowering in rice†.</td>
<td>Upper limit of max temperature for milk production is 27°C§</td>
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<tr>
<td>Precipitation</td>
<td>Seasonal</td>
<td>low rainfall during the growing season can have a detrimental impact on productivity (e.g. Ganges), conversely high rainfall can lead to flooding in some areas (e.g. Brahmaputra basin). Excess water from prolonged periods of rain can lead to soil water logging, anaerobicity and reduced plant growth†.</td>
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<tr>
<td>Runoff</td>
<td>Seasonal</td>
<td>changes to seasonal flows could affect the availability of water for irrigation and domestic use particularly when flows are very low or even cease flowing completely during the dry season†.</td>
<td></td>
</tr>
<tr>
<td>Hydro-power</td>
<td>Temperature</td>
<td><strong>Seasonal</strong> – rising temperatures could impact energy demand, particularly during warmer periods of the year, this could mean a greater demand for energy for cooling. This could translate into a high demand during periods with low flow and therefore reduced supply‡.</td>
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<td><strong>Annual</strong> – changing patterns in precipitation and runoff could mean hydro-power is more or less viable‡.</td>
<td>Minimum flows needed to sustain a healthy river ecosystem are different for each river.</td>
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<tr>
<td></td>
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<td><strong>Seasonal</strong> – changes in seasonal cycles of precipitation and glacial melt could result in large changes in riverflows with some rivers completely drying up in the low flow months and others very high during peak flows, thus having implications for hydropower‡.</td>
<td></td>
</tr>
<tr>
<td><strong>Health and housing</strong></td>
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<td>Seasonal - rising temperatures could affect the population directly through heat stress or indirectly through changes to the spread of pests and diseases.</td>
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<table>
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<th>Annual</th>
<th>Seasonal (JJAS)</th>
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<td></td>
<td>Min</td>
<td>Mean</td>
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<td>Temperature (°C)</td>
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<tr>
<td>Precipitation (mm per day)</td>
<td>-1</td>
<td>0.2</td>
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<tr>
<td>Runoff (mm per day)</td>
<td>-0.2</td>
<td>0.2</td>
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</tbody>
</table>
High resolution multi model climate change scenario over India including first uncertainty assessment

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\textbf{ABSTRACT}

This study presents the possible regional climate change over South Asia (SA) with a focus over India as simulated by three very high resolution regional climate models (RCMs). First the ability of RCMs to simulate the monsoon climate is analyzed. For this purpose all the three RCMs are executed with ECMWF reanalysis data for the period 1989-2008 at a horizontal resolution of \~\!25km. The results are compared against independent observations. In order to simulate future climate the models are driven by lateral boundary conditions from two global climate models (GCMs: ECHAM5-MPIOM and HadCM3) using SRES A1B scenario, except for one RCM, which only used data from one GCM. The results are presented for full transient simulation period 1970-2099 and also for the time slices 1970-1999, 2021-2050 and 2070-2099. The analysis concentrates on precipitation and temperature over land. All models show a clear signal of
gradual wide-spread warming throughout the 21st century. The ensemble-mean warming evident at the end of 2050 is 1°C-2°C, whereas it is 3°C-5°C at the end of century. The projected pattern of the precipitation changes shows considerable spatial variability. With an increase in precipitation over the peninsular India and coastal areas and, either no change or a decrease over areas further inland. The influence of the driving GCM on the projected precipitation change simulated with each RCM is as strong as the variability among the RCMs driven with one GCM. Some results of the first uncertainties assessment are presented.

INTRODUCTION

The global climate is both variable and changing on a range of temporal and spatial scales. The notion that mankind ‘very likely’ has an influence on the global climate that is discernible from the natural variability at seasonal and decadal time scales on the global mean climate (Intergovernmental Panel on Climate Change IPCC, 2007) has raised the concern about our vulnerability to various aspects of this climate variability. Various assessments of IPCC and many summaries and interpretations on climate change and climate variability have been published. These provide an increasingly detailed picture of the variations of many different atmospheric variables for example temperature, precipitation, atmospheric humidity, soil moisture.

The nature, amplitude and predictability of this variability strongly depend on the spatial or temporal scales being considered. The global mean climate changes in response to variations in the solar forcing, the amplification of these responses within the climate system due to feedbacks (like air sea interactions feedback over tropics), internal
oscillations of large scale phenomena (like El Niño Southern Oscillation, ENSO), the composition of the atmosphere (that varies with volcanic activity and greenhouse gas emissions) and the biophysical state of the land surface and oceans. On the \textit{regional scale} (defined here as areas of the size of subcontinents or a country as a whole) climate variability is further enhanced by variations in the atmospheric circulation and local land-atmosphere feedbacks.

Adaptation to climate change and variability is not a new phenomenon, however the increasing awareness of human influence on global climate have changed behaviours and perspectives significantly. For example water managers have been adapting to short term variability for many years by taking precautions against the impacts of imminent rain storms. However, adaptation at longer timescales is now being recognized as increasingly important. The most relevant horizons of climate variability for the water sector are:

- the \textit{synoptic time scale}, where individual weather systems may result in extreme hydrological events,
- the \textit{seasonal time scale}, where persistent anomalies in precipitation may accumulate in enhanced risks for droughts or flooding,
- the \textit{decadal time scale}, where an outlook of global and regional trends during the coming decades are relevant for planning and implementing water resource management measures, and
- the \textit{century time scale}, where changes in the mean (say, 30 year average) climatology of meteorological variables may affect the design of hydrological infrastructure for safety, traffic or water resources.

One may view climate variability as a combined result of different processes acting on different time scales, for example, synoptic weather events are affected by atmospheric circulations and local feedbacks. Seasonal anomalous weather is related to
large scale variations in Sea Surface Temperature (SST) or stored soil moisture and snow. Changes at even longer time scales are related to the slow variations in the ocean heat content and large scale changes in the atmospheric composition. However, there is a clear link between the short and the longer time horizons (Palmer et al, 2008). The response of local weather to a major SST anomaly like an El Niño event is not equally strong in all places of the world. A good prediction of this local weather response requires a good representation of the short-term variability and local processes. Likewise, projections of the change in global mean temperature in the next couple of decades are dependent on the assumptions of the amount of heat stored in the ocean, which depend strongly on atmosphere-ocean interactions at much shorter time scales. In the last few decades the frequency of El Niño events has increased which has had a large impact on seasonal precipitation and temperature anomalies across the entire world. As a result of this, awareness has grown that adequately addressing climate variability at the seasonal time scale may help to anticipate climate change at longer time scales.

Global climate models have been developed to study the Earth’s climate system in the past and future, driven by assumptions on the evolution of drivers of climate change. The drivers are, for example, amount and distribution of aerosols and greenhouse gases (GHG) in the atmosphere, which depend directly on natural and man-made emissions. As part of IPCC AR4 possible developments of the socio-economic system (Nakićenović et al. 2000) were used to produce story lines of future emissions. These emission scenarios are an attempt to address the uncertainty in future emissions which are an important aspect of assessing future climate conditions. These emissions scenarios are translated into greenhouse gas concentrations, used by GCMs to make projections of future climate. The IPCC AR4 produced a large GCM ensemble of projections, to account for the limited skill of GCMs and that the model structure forms an important second source of
uncertainty. Both scenario and GCM model uncertainty result in an increasing spread of the projection of global mean temperature changes, up to a range between 1.5°C and 5.5°C in 2100 (IPCC, 2007).

GCMs are mathematical representations of the Earth system, in which physical and biogeochemical processes are described numerically to simulate the climate system as realistically as possible. Considerable research comparing GCM results to independent observations have allowed rapid model development and the subsequent improvement of the models. An ensemble of past episodes is simulated and the results are compared against measurements before the models are used for climate change studies. Another source of uncertainty, highlighted by the use of an ensemble of model simulations is the internal variability in the climate system that is inherently present and cannot be avoided, even if perfect models were possible. The individual ensemble members are usually in good agreement with atmospheric analyses (e.g. ERA Interim-analyses, which has been reconstructed using a large set of observations in a global modelling system. This data-set can be seen as close to reality as possible using state of the art tools) but sometimes show a systematic bias, e.g. being about 0.5 ° warmer than the reconstructed observations for members of the global coupled climate modelling system ECHAM5-MPIOM (not shown here). The observed increase during the last decades is clearly visible in the GCM simulations (see also IPCC WG 1 report, 2007). GCMs provide information at a coarse spatial resolution which is often not suitable for regional climate change assessments. Also the spatial variability at these regional scales (where “regional” refers to a domain of typically 500 – 1000 km in this section) is much larger than for the global mean climate thus introducing another source of uncertainty.

In order to translate global model information down to the regional scale two principles can be applied. *Statistical downscaling* techniques use an observed relation
between large scale phenomena (often fairly well represented in coarse scale GCMs) and local quantities (like daily precipitation or daytime temperature). This relation is subsequently applied to GCM output to obtain local and regional climate change signals. A major disadvantage of this approach is the implicit assumption that the calibrated relationships for present-day climate conditions are also applicable to future climate conditions. This is debatable when climate change leads to significant different climate regimes.

*Dynamical downscaling* uses high resolution RCMs, which are nested within GCMs (Jacob, 2008). Large scale phenomena are inherited from the host GCM, but additional detail is provided concerning the land use, coast lines, topographical structures and better resolved spatial gradients in physical fields (see Fig. 1). This additional information can alter the regional flow pattern substantially and give more credit to local feedback processes like snow-albedo/temperature or soil moisture/temperature feedback. RCMs therefore generally improve on the higher order statistics of the meteorological variables. One potential drawback of some RCMs is their large demand on computer resources and the complexity of their operation, which requires trained staff. However, dynamical downscaling methods are increasingly being used, and will be discussed in more detail below.

In this paper we explore climate variability and change, and its predictability at the seasonal and decadal time scales over India. We argue that an adequate awareness of tools and knowledge concerning the seasonal time scale may increase our ability to deal with climate variability at longer time scales. Section 2.1 will address the observed recent changes in some relevant climate variables which are compared to natural variability, concluding with the notion that on the multi-year time scales climate change is ongoing and detectable. The models and data used in this study are described in section 2.2. In
section 2.3 we focus on the general and seasonal predictability in terms of the IPCC AR4 GCM ensemble. Section 2.4 analyses the very high resolution RCM simulations over India and its projections towards the end of 21st century. Tailored regional climate information is presented in section 2.5 and finally the conclusion and future prospective.

2.1 CLIMATE INFORMATION CHAIN OVER INDIA

Climate is changing with time as is witnessed by various observations data sets in the last century. IPCC Fourth assessment report (2007) have reported that surface air temperature has a linear trend (1906-2005) of 0.74 (0.56 to 0.92) °C and is larger than the corresponding trend of 0.6 (0.4 to 0.8) °C (1901-2000) given in the IPCC Third Assessment Report (2001). Figure-2 shows the air temperature anomaly over India for the period 1901-2009 based on CRU gridded data. Figure-2 illustrates that there is a statistically significantly trend approximately 0.45° C for this period compared to the 20th century period, 1901-1930. Using the period 1961-1990 the rise is approximately 0.30 C a statistically significant change at the 95%level. Table-3 shows the decadal average temperature over India for the period 1901-2009. The time series shows a substantial increase in the last three decades with the last decade (2000-2009) the warmest on the record, increasing by 0.580 C compared to normal 1961-1990. The warmest year of the time series was 2009 (1.110 C above normal 1961-1990). Between 1980 till now (2009) the air temperature is above normal (1961-1990) in all except few years (1983, 1984, 1989, 1992, and 1997). The coldest year of the time series is 2005, the coldest year in the 21st century but is still in the line of the warmest year of the whole time series.

Based on the Koeppen-Trewartha climate classification, the climate of India is mainly characterized by a tropical humid to sub-tropical summer wet season with dry
semi-arid to arid over northwest India (Trewatha 1954, Jacob et al. 2012). During the summer monsoon season (June-September: hereafter referred as JJAS), the country as a whole receives 70% - 90% of its annual rainfall (Pant and Rupa Kumar, 1997), whereas October to May is more or less a dry season, except during north-east monsoon (Kumar et al. 2007) when the south peninsular of India particularly the east coast receives a good amount of rainfall due to the western Ghats casting a rain shadow. Summer monsoon rainfall over the whole India does not show any increasing or decreasing trend though there are trend on a regional scale over various meteorological sub divisions of India. IPCC (2007) suggested that extreme events are likely to be increased over SA. This has been observed in the increasing trends of extreme precipitation events over the west coast of India and north western parts of peninsular India (Joshi and Rajeevan, 2006). One event that caused widespread devastation was the heavy rainfall event on the 26th July 2005 (944 mm in one day) over Mumbai which resulted in heavy flooding in the city, at least 1000 casualties with a preliminary financial cost of nearly nine million dollars. This event is one example, which shows how a single event in a very short span of time can have a local impact. Although a single event cannot be directly attributed to climate change an increasing trend in these types of events could indicate changing patterns and distribution of extreme events.

Under increasing greenhouse gases scenario the climate of India is predicted to be wetter and warmer (IPCC 2007, Rupa Kumar 2006). However Ashfaq et al. 2009 have also suggested that the monsoon rainfall over south Asia is likely to be suppressed by the end of this century, however they do have report some limitations in their study.

2.2 DATA, MODELS and EXPERIMENTS
2.2.a Data

Two sets of observational precipitation and temperature data (Table-1) have been used to analyze the robustness of the model simulation results:

(i) the observational data (CRUv3.1) of precipitation and surface air temperature (2m) used to validate the model results have been taken from British Atmospheric Data Centre, which covers the entire global land points, at a horizontal resolution of 0.5° X 0.5° (hereafter referred as CRU) for the period 1901-2009 and has been analyzed extensively by Brohan et al. 2006.

(ii) Precipitation data from the India Meteorological Department (IMD) at 0.5° X 0.5° (Rajeevan and Bhate 2008), have been used to assess the model results over India for the period 1971-2005.

(iii) Mean, maximum and minimum temperature data from IMD 1° X 1° (Srivastava et al. 2008), have been used to assess the model results over India for the period 1970-2005.

For the GCMs study over south Asia 22 IPCC AR4 models data have been used (Kripalani et al. 2007). The parameters which are analyzed in this study are precipitation and 2m air temperature for full transient period 1901-2099 and for the three time slices (i) 1970-1999 for the 20c3m historical simulation, (ii) 2021-2050, (iii) 2070-2099, both for the A1B scenario.

2.2.b Models

The REgional MOdel (REMO) is a three dimensional hydrostatic atmospheric circulation model, which solves the primitive equations of atmospheric motion. REMO (Jacob, 2001, 2009) is a combination of two models, the dynamical core and discretisation
in space and time have been taken from the Europa Model of the German Weather Service (DWD) and the Physics has been taken from the GCM ECHAM4 (Roeckner et al. 1996). The atmospheric prognostic variables of REMO are horizontal wind components, temperature, pressure, specific humidity, and cloud liquid water content. The model uses the Arakawa-C grid for horizontal representation in which all variables except the wind component are defined in the centre of the respective grid box, and a hybrid of $p$ and $\eta$ using 27 levels in vertical. The vertical discretisation follows Simmons and Burridge (1981). The lateral boundary interpolation uses the method of Davies (1976). The prognostic variables of REMO are adjusted towards the large scale forcing in a lateral sponge zone of 8 grid boxes in which the lateral boundary conditions (LBC) influence decreases exponentially towards the inner model domain.

In principle, soil hydrology processes in REMO are derived from the parameterization scheme of ECHAM4 (Roeckner et al. 1996). The land surface scheme in REMO is taken from Dümenil and Todini (1992) and Hagemann and Dümenil Gates (2003). The soil temperature over land is calculated using a diffusion equation solved in five different layers ranging down to 10m in the lower most soil. The grid scale parameterization of cloud microphysics is based on the solution of the budget equations with the bulk scheme of Kessler (1969) and sub grid scale precipitation processes follow the Tiedtke (1989) convective scheme, with adjustments to Nording (1994). The temporally constant vegetation dependent land surface characteristics are taken from the LSP2 dataset (Hagemann 2002). The surface mean orography is calculated from USGS GTOPO30 topography data. The seasonal cycle of vegetation is represented by monthly varying fields of LAI, fractional green vegetation cover (Rechid and Jacob 2006) and snow-free land surface albedo (Rechid et al. 2008a, b).
REMO was run on climate mode with a horizontal resolution of 0.25° (~25 Km) using a slightly modified version of the physical parameterization scheme in ECHAM4. With climate mode, the model has to be initialized once and uses surface parameters over land, SST over ocean and varying lateral boundary values during the whole simulation. The lateral boundaries are updated with a 6-hourly temporal resolution interpolated into a 2 minute time step. The model domain over South Asia is 60.125E - 100.125E and 4.125N – 40.125N, with 27 vertical levels (i.e. 181 x161 grid points). Figure-1 shows the model domain and the topography over SA.

HadRM3 was run on a rotated pole grid at 0.22° (~25 km) on a 213 by 189 grid covering a domain from 59E, 0N to 41N, 110E. The configuration utilizes 19 levels in the atmosphere. HadRM3 is a regional version of the HadRM3 global atmosphere model and therefore relies on surface boundary conditions from SSTs over the ocean and a land surface model. The version of HadRM3 uses an updated version of the land surface scheme. Lateral atmospheric boundary conditions are updated from ancillaries 3-hourly and interpolated to a 150 second time step.

2.2.c Experiments

RCMs (HadRM3 and REMO) simulations used in the present study are performed under EU FP7 project “HighNoon”. The HighNoon RCMs climate simulations provide data at horizontal resolution of ~25 km. The RCMs simulation are designed as (i) form 1989-2008 using lateral boundary conditions (LBCs) from ECMWF reanalysis product ERA-Interim (Simmons et al. 2007, hereafter referred as ERAI) (ii) from 1950-2000 using LBCs from two IPCC AR4 GCMs (Max Planck Institute for Meteorology GCM ECMAM5-MPIOM [hereafter referred as ECHAM5] :3rd realization, Rockner et al. 2003) and HadCM3, (the Third Version of the Met Office Hadley Centre Climate Model, Pope
et al. 2000, Gordon et al. 2000) historical simulation (20c3m) (iii) form 2000-2099 using LBCs from both GCMs SRES A1B scenario (Nakićenović et al. 2000). The third RCM (CCLM) used in the study uses LBCs from one GCM (ECHAM5). The simulation results are presented for the ensemble mean of all RCM simulations for India. The ensemble-mean results can help to quantify uncertainties in future climate projections.

The orography plays a very important role in modulating the Indian summer monsoon rainfall (ISMR). Figure-1 shows the influence of horizontal resolution on ISMR. The orography (upper panels) and the ISMR (lower panels) for the period 1970-1999 are presented for the climate models. The GCMs because of their course horizontal resolution fails to simulate the orographic rainfall whereas RCM due to very high horizontal resolution (~25km) represent the ISMR reasonably well (ensemble mean of five RCMs). For example, the orographic rainfall over west, central east coast and NE India is well represented by the RCM than driving GCMs. The rainfall maxima over central India and rain-shadow area over east coast of India are also well captured by the RCMs. Table-2 gives the details of RCM simulation performed for this study.

2.3 CLIMATE OF INDIA IN GCMs

Over south Asia, several GCMs studies focus on the Indian monsoonal region and most conclude that GCMs have difficulties in simulating the mean monsoon climate of India. GCMs have a course horizontal resolution (~200Km) and therefore have limitations in simulating the complex orographic precipitation over India (Sperber and Palmer 1996, Giorgi 2002, Kang et al. 2002, Douville 2005). The IPCC AR4 (2007) ensemble has provided a comprehensive set of models for monsoon studies. The present day climate simulated by 21 of the IPCC AR4 models shows large cold and wet biases when
compared to observations over south Asia. The ensemble mean temperature cold bias is 
\(\sim 1.5^\circ C\) whereas an individual model analysis shows that this bias is of the order of \(6^\circ -7^\circ C\) in the same models. The precipitation bias is less compared to temperature. However, limited observations over this region restrict the proper validation of the models (IPCC 2007). IPCC multi model projection under A1B scenario projects an increase in annual mean precipitation over India. Though half of the models predict an increase and the other half say no change in monsoon precipitation over most of India towards the end of 21st century, the major agreement among GCMs is over south peninsular of India where nearly 75% of models project an increase in monsoon precipitation and nearly 30% suggest a decrease over NW India (Figure-11.9, IPCC 2007). These projections are in line with earlier GCMs projections over the region (Rupa kumar et al. 2002, 2003, May 2004). The IPCC AR4 GCMs control climate simulations results show a systematic cold temperature bias over south Asia whereas projected surface temperature suggest a warmer climate. This temperature change over land leads to an enhancement of land-sea thermal contrast in summer and weakening during the winter. The Monsoon dynamical circulation is likely to weaken under the A1B the warming scenario towards the end of 21\textsuperscript{st} century (Ashrit et al. 2003, Ueda et al. 2006), however increases in GHG forcing and the subsequent rise in temperature could leads to larger moisture fluxes and more precipitation. Analysis of the IPCC AR4 GCMs shows that only 6 GCMs of a subset of 18 (Annamalai et al. 2007) are able to capture the pattern correlation of precipitation between models and CMAP observations with a smaller root mean square difference compared with observations over India (7N – 30N & 65E – 95E) and a larger monsoon domain (25S – 40N & 40E – 180E). Kripalani et al. (2007) show that only 7 models of a subset of 22 IPCC AR4 GCMs over India (5N – 35N & 65E – 95E) capture the mean annual cycle, shape and magnitude
compared with observations. Annual cycles of precipitation of some selected models are similar to the observed ones but have spatially substantial quantitative biases.

In the analysis, we consider the ensemble mean of 22 IPCC AR4 GCMs (hereafter referred as GCM_{EM}) averaged over India is analyzed for the parameters precipitation and 2m air temperature. Figure-3 shows the GCM_{EM} of precipitation for monsoon season. The time-series shows 1901-1999 the historical period (20c3m) and 2000-2099 for the SRES A1B scenario. The GCM_{EM} precipitation is underestimated in comparison with observational data (IMD and CRU), however their spread is very large leading to a smoothed mean value. For the period 1970-1999 the GCM_{EM} is ~22% and ~37% less than CRU and IMD respectively and as expected the interannual variability (standard deviation) of GCM_{EM} is very less compared to observations (Table-3). Figure-4 is same as Figure-3 but for 2m air temperature. GCM_{EM} have systematic cold bias compared to observational data approximately ~4 oC and ~6 oC with CRU and IMD respectively. Though GCMs have shown a systematic cold bias but the interannual variability (0.17 oC) is fairly well simulated compared to observations (IMD and CRU both 0.26 oC).

GCMs such as ECHAM5 and HadCM3, identified by Annamalai et al. (2006) as models which capture the mean monsoon value and inter-annual variability better than the other IPCC AR4 models are used to force the HighNoon RCMs simulations.

Figure-5 shows box-and-whisker plots of all the IPCC AR4 GCMs future projections with respect to control climate (1970-1999) for two time slices 2021-2050 and 2070-2099 for all models SRES A1B scenario and realization over south Asia (40E to 100 E and 4N to 40N). The x-axis represents the precipitation in percentage and y-axis 2m air temperature in oC. The colored dots shows the position of GCMs ECHAM5 (red) and HadCM3 (blue) which are used in the present study to provide large-scale information to the regional climate models. HadRM3 is relatively cooler than ECHAM in 2070-2099,
however all the models show an increase in precipitation and temperature, the ensemble median increase in precipitation is approximately ~5% (~10%) by the mid (end) of this century Figure-5 (a & b) and for temperature the increase is approximately ~1.5°C (~2.5°C) compared to control climate.

Since ECHAM5 and HadCM3 are used to force the regional climate models simulations in this study therefore, for their ensemble mean (hereafter referred as GCM\textsubscript{FEM}) spatial patterns of precipitation and temperature are presented for later comparison with RCMs projections. HadCM3 data is interpolated to ECHAM grid. Figure-6 upper panels show the GCM\textsubscript{FEM} precipitation (JJAS) future projections with respect to control climate (1970-1999) for the two times slices 2021-2050 and 2070-2099. An increase of 5%-10% is projected over Indo-Gangetic plains and 15%-30% over NW India, however a weak reduction of approximately ~5% is projected over peninsular India. By the end of 21\textsuperscript{st} century the increased precipitation over Indo-Gangetic plane could intensify further whereas the decreasing precipitation over the peninsular India could remain the same but with smaller spatial area. Figure-6 (Lower panels) shows the projected warming under increasing greenhouse gas scenario A1B. Air temperature warming is uniform and widespread. By 2021-2050 the spatial warming could be between 1°C to 1.5°C over whole of India for this ensemble. For the period 2070-2099 the mean warming is more pronounced especially over northern India and Himalayan region, possibly between 3°C to 4.5°C.

2.4 REGIONAL MODEL SIMULATION OVER INDIA
As for GCMs, the model quality of RCMs needs to be analysed before addressing climatic change study. We use a reanalysis product to provide boundary information to the models. Reanalysis products contain both model information and observations therefore providing the best estimate of the atmosphere. Lucas-Picher et al. 2011 evaluated a set of four regional climate models and have suggested that models are able to represent the monsoon climate better than the driving fields but they do have certain limitations over the region. Here we use an RCM ensemble which uses ECMWF reanalysis data for large-scale boundary information to provide an ensemble mean (hereafter called as RCM\textsubscript{REM}) for the period 1989-2008 which is compared against independent observations. Figure-3 (blue dotted lined) shows the JJAS annual mean precipitation climatologies of RCM\textsubscript{REM}. The RCM\textsubscript{REM} shows good agreement with observations (IMD and CRU) in capturing the year to year monsoon variability. The climatological mean of RCM\textsubscript{REM} is 6.7 mm/d and standard deviation is 0.38 mm/d whereas observation CRU mean is 5.6 mm/d and standard deviation 0.45 mm/d. The other observational data IMD climatological mean is always more than CRU (Table-3). So, RCM\textsubscript{REM} is lying in between the both observational data sets (Fig-3). RCM\textsubscript{REM} is able to capture the magnitude as well as the inter-annual variability quite well. Also all the important spatial characteristics (Figure not shown) of summer monsoon rainfall over India, like high convective orographic precipitation over west coast, central east coast, foot hills of Himalayas and land rainfall maxima as well as rain-shadow area over east coast of India are well simulated by the RCMs. The inter-annual variability of RCM\textsubscript{REM} for 2m air temperature shown in Figure-4, illustrates that RCM\textsubscript{REM} capture the year to year variability is reasonably well simulated but the magnitude of RCM\textsubscript{REM} is slightly less than the observations. IMD/CRU/RCM\textsubscript{REM} is available at ~111 km/~55 km/~25 km horizontal resolution, so by increasing the horizontal resolution temperatures are showing
lower values (Fig-4). Therefore it is very hard to say RCM\textsubscript{REM} has large cold bias against the observations or is due to observations limitations both in space and resolution. It is very clear the RCM\textsubscript{REM} has shown good skill in capturing the mean monsoon climate.

The precipitation inter-annual variability results simulated by ensemble mean of RCMs provided with large scale information at the boundaries from ECHAM5 and HadCM3 (hereafter referred to as RCM\textsubscript{EM}) for the control climate (1970-1999) is well simulated when compared to observations (IMD and CRU) Figure-3. The spread of the RCM ensemble is smaller than the GCM AR4 ensemble as it has fewer members. Further the transient time-series suggest an overall gradual increase in monsoon precipitation over India by the end of 21\textsuperscript{st} century. The RCMs simulated the monsoon precipitation much better than the driving GCMs, this is illustrated by the increased rainfall in the RCM\textsubscript{EM}. The monsoon season climatology of RCM\textsubscript{EM} (6.4 mm/d) is ~30% more than the GCM\textsubscript{EM} (4.5 mm/d) for the control period (Table-3). With respect to observation RCM\textsubscript{EM} is showing 12% more than CRU and 10% less than IMD. The standard deviation of RCM\textsubscript{EM}/GCM\textsubscript{EM} is 0.31/0.09 mm/d and observation CRU/IMD is 0.61/0.65 mm/d. Thus RCM\textsubscript{EM} showed better skill in capturing the mean monsoon climate than the driving GCMs and reproduced the inter-annual variability well. For the period 2010-2039, 2040-2069, and 2070-2099 RCM\textsubscript{EM}/GCM\textsubscript{EM} showed an increase in precipitation by ~6%/~2%, ~10%/~6%, and ~14%/~8% respectively. This shows that precipitation could increasing into future together with the variability in rainfall (shown by increasing standard deviation) thus suggesting a possible increase in extreme rainfall events.

The transient time-series of RCM\textsubscript{EM} for temperature shows that the RCMs capture the interannual variability reasonably well compared to observations although the magnitude is systematically less, which is same as the GCM\textsubscript{EM}. The cold bias present in the driving GCMs affects the RCM simulations, this is illustrated by the RCM simulations
which use ERAI boundary data, which compares much better to observations than RCM forced with GCMs. The IPCC AR4 (2007), GCMs have a large cold bias over south Asia. Annual 2m temperature change of RCM_{EM}/GCM_{EM} for the period 2010-2039, 2040-2069, and 2070-2099 with respect to control climate is 1.0°C/1.0°C, 2.3°C/2.2°C, 3.6°C/3.2°C respectively. Whereas annual mean increase in precipitation by the end of 21st century for RCM_{EM}/GCM_{EM} is ~15%/~11%.

The projected spatial pattern of precipitation for monsoon season is shown for the two time slices 2020-2050 and 2070-2099 with respect to control climate. In Figure-7 vertical lines represent the region where the climate change signal is statistically significant and the symbol * denote the region where 4 or more member out of five RCM simulations agrees the sign of change. Figure-7 shows that rainfall is likely to increase over peninsular India, Gujarat, and parts of Rajasthan and Jammu-Kashmir for the 2021-2050 compared with 1970-1999. The signal is mainly robust (10%-20%) over peninsular India especially over the west coast, where maximum simulations agree on the sign of change and are statistically significant. This robust signal intensifies further (20%-40%) by the 2070-2099 period (Figure-7). However, for this time slice the increase in precipitation over Rajasthan has changed sign from an increase to a decrease by 5%-10% and even more in further NW direction. A new region with statistically significant increase in precipitation emerges over the plains of northern and northeastern India, Himalayan mountainous region, Bangladesh and Myanmar for 2070-2099 period. Most of the spatial increase/decrease signals over India by the end of 21st century are in line with the earlier study (Rupa Kumar et al. 2006) using the A2 and B2 SRES scenario. The IPCC AR4 (2007) multi model projection for India suggests an overall spatial increase in monsoon precipitation (JJA) by the end of 21st century. One interesting feature of this study is that the RCMs are modifying the regional projection compared to their driving
GCMs. The driving GCM\textsubscript{EM} projected (Figure-6) an increase in precipitation over central and northern India, whereas, RCM\textsubscript{EM} shows more or less opposite signal. The GCM projection also suggests very little change (up to ~5%) over peninsula. The RCM\textsubscript{EM} projections show a robust statistically significant increase in precipitation over the region. The decrease in precipitation over NW India and further is not supported by forcing GCM\textsubscript{EM}, however, the monsoon rainfall over this region is very minimal and small changes in their projected magnitude will show very large interannual variability. This is not the case for Western Ghats where sufficient precipitation is received during the monsoon season.

The 2m temperature climatologies simulated by the model is shown in Figure-8. The warming is widespread though the magnitude differs spatially. For the time slice 2021-2050 RCM\textsubscript{EM} suggest a wide spread warming in the range of 1.5\textdegree C to 2\textdegree C. In the simulations using the A1B scenario, this signal intensifies further by the end of the century in the range of 3\textdegree C to 4.5\textdegree C. In winter (DJF, figure not shown) the warming is the largest over the Himalayan region and the magnitude of the warming is stronger than summer. The winter signal, therefore dominates the annual signal.

2.4.a Tailored climate scenarios

The chain of information on possible future climate developments starting with a range of greenhouse gas scenarios, running an ensemble of GCMs and downscaling via regional climate models or statistical post processing is characterized by a continuous increase in volume of numbers and possible pathways. For users in professional sectors with interest in future climate evolutions, further guidance, data reduction or data transformation is needed. It is the rule rather than the exception that general climate
change scenarios, even at the regional scale, need additional “tailoring” to meet the user’s needs.

This process of tailoring encompasses a wide range of procedures. For example, it can be the outcome of a discussion on the choice for the most relevant scenario for a given sector from an available plume. It can be a quantitative translation of a meteorological variable (like the change of the daily mean temperature at the average hottest day in the year or season) into a quantity that is more related to the concerned sector (like the likelihood of having temperatures excess with respect to a respective threshold may harm the development of insects present in an ecological food chain or may increase in malaria cases etc.). It can be a detailed time series of daily precipitation at a given location consistent with assumptions about the future climate developments, needed to test sewage design. Or it can be the change of the likelihood of extreme storm surges with return periods much longer than the observational record, to be derived from the general scenario data by means of statistical extrapolation of extreme events.

As an example, the annual time series over India for minimum and maximum surface temperature are analysed in terms of frequency of warm/cold days for the control climate (1970-1999) and compared against observation IMD. For the present study, RCM ensemble mean future projections with respect to present climate are analyzed for the period 2000-2099. Similarly, warm/cold nights are also analyzed. Extreme temperature indices can be considered using several criterions like using an arbitrary threshold value (Jones et al. 1999) or by using the percentile (p) method (Plummer et al. 1999, Kothawale et al. 2010). India has a large geographical coverage and hence its climate varies geographically (Pant and Rupa 1997), therefore using an arbitrary threshold will not provide a realistic representation for the country as a whole. In this study percentile thresholds have been used to define the extreme temperature indices as described in
Kothawale et al. (2010). Extreme temperature indices for warm/cold days and nights have been prepared using daily time series of minimum (TN) and maximum (TX) surface temperature for the present period. Extreme temperature indices are defined on the basis of monthly percentile values and the seasonal cumulative for each year. The following definition has been used to prepare climate indices

(i) hot days = TX > 90p
(ii) hot nights = TN > 90p
(iii) cold days TX < 10p
(iv) cold nights TN < 10p.

According to the above definition, hot days are defined as the frequency of warm days exceeding the 90th percentile for that particular month(i) and the annual monthly cumulative provides the number of warm days for that particular year; similarly other indices are also calculated. To observe the possible changes in the future extreme patterns (2000-2099), thresholds from the control period simulation (1970-1999) have been used to see the relative changes with respect to present day climate. The rx5day indices is the 5-day consecutive mean maximum precipitation in each year using daily precipitation data to generate an annual time-series for both present and future climate. Figure-9 depicts the yearly annual frequency of extreme temperature indices for observations (IMD) and RCM_{EM} over India for the control climate. RCM_{EM} is able to capture the observed extreme temperature variability very well. The most important and the interesting result is that regional model is able to capture the signature of trend (±) and magnitude for all the calculated indices similar to that observed. Mann-Kendall trend test has been used for significance test of indices. Both, IMD and RCM_{EM} show an increasing trend for hot nights/days that is not statistically significant, however RCM_{EM} mean showed a significant increasing trend (at the 95% confidence level) in the number of hot
nights. IMD cold nights/days show a decreasing trend of the order of ~4.5 days/decade, RCM\textsubscript{EM} mean also captured the same decreasing trend and is 2.95/1.95 days/decade. Both IMD and RCM\textsubscript{EM} cold days decrease are statistically significant at 90% level. However the lower magnitude in the RCMs projections could be due to a cold bias in the model (Figure-4). Table-3 gives detailed information all five of the calculated extreme indices calculated. The precipitation indices rx5day of IMD show an increase 4.1 days/decade and RCM\textsubscript{EM} increase of 3.42 days/decade, however increasing trend in IMD is not significant and the increasing trend in RCM\textsubscript{EM} is significant at 95% level. The possible expected changes in future extreme frequencies are also examined based on control period percentile value. Figure-9 depicts all the RCM\textsubscript{EM} control and future extreme indices. Hot nights/days are likely to be increased and are statistically significant at 99.9% confidence level. Hot nights/days showed their frequency might increase by 9.15/13.65 day/decade. Similarly cold nights/days showed a sharp decreasing trend of 2.93/2.82 days/decade with respect to their control climate and the trend is statistically significant at 99.9% confidence level. By the end of 21\textsuperscript{st} century the cold nights/days are almost zero compared to the present climate. The future projected rx5day of RCM\textsubscript{EM} suggest an increase in daily intensity of precipitation over India under A1B scenario by the end of 21\textsuperscript{st} century thus suggesting extreme precipitation events might increase.

### 2.5 CONCLUSIONS AND PERSPECTIVES

The translation of climate change information to impact assessment involves many complex processes and is very often non-linear, which means that a 10% increase in precipitation is not automatically a 10% increase in water resources, for example.
Therefore, the construction of regional climate change scenarios and the interpretation of their results need special attention.

This analysis discusses simulation of precipitation and temperature over India for the present and future climate using the ensemble mean of IPCC AR4 GCMs and three very high resolution (~25 km) RCMs.

The climate of India is changing under changing global climate. The 2m air temperature since 1901 show an overall increase (2009) of 0.45° C in temperature. This increase is highly statistically significant in the last three decades and particularly last decade 2000-2009 the rise is 0.58° C compared to normal 1961-1990. The year 2009 was warmest on the time series, with temperature 1.1° C above normal. Since 1993 air temperatures are above normal (1961-1990) except one year. Monsoon rainfall as a whole does not show any significant increasing or decreasing trend but earlier studies suggest that extreme temperatures over west coast and northern parts of peninsular India show a significant increase (Joshi and Rajeevan 2006).

Analysis of the ensemble mean suggests that GCM_{EM} were able to simulate the mean JJAS climatology of surface parameters and were able to capture the broad scale features of Indian summer monsoon, for example, seasonal migration of convection belt to the north of India. However the models have substantial quantitative biases mainly due to their course resolution. The GCM_{EM} control climate 2m air temperature has a cold bias of nearly 6° C compared with observations. The future projections using the A1B scenario suggest a wide spread warming (~3.2° C) and overall increase (~11%) in mean monsoon precipitation by the end of 21st century.

The RCM_{REM} forced with ECMWF reanalysis showed good skill in simulating the past climate of India, for example, RCM_{REM}/CRU precipitation for the monsoon season is 6.7 mm/d/5.6 mm/d, IMD is more than CRU (Table-3) so RCM_{REM} is lying between the
observation data. Temperature of $\text{RCM}_{\text{EM}}$/CRU is 22.5° C/23.1° C which is also in well agreement, thus improving the higher order statistics over India. $\text{RCM}_{\text{EM}}$ showed good skill by capturing all the regional spatial regimes quite well mainly the regional orographic precipitation patterns.

$\text{RCM}_{\text{EM}}$ forced with GCMs showed better skill than GCMs in simulating the inter-annual variability of the mean monsoon precipitation. The magnitude of the RCM temperature and precipitation is quite close to observation data sets (Fig-3), however the temperature has a systematic cold bias which is the same as the GCM (Fig-4) which may also explain the lower precipitation. The $\text{RCM}_{\text{EM}}$ climate projection over India using SRES A1B scenario suggest a wide spread warming throughout the year though the spatial distribution in winter and summer are different. In winter the warming is largest over the Himalayan region (4° C - 6° C), however for the whole of India the warming could be between 3° C to 4.5° C with a maximum over central and west India. In, summer the largest warming is projected for the central and northern India and over major parts of the Himalayan region of between 3.5 ° C to 4.5° C. The warming for the southern India is projected to be slightly lower (~2.5° C). This is an interesting result as IPCC (2007) multi model projection over south Asia as well as this study GCM suggests maximum warming over Himalayan region throughout the year, where $\text{RCM}_{\text{EM}}$ suggest seasonal spatial changes in maximum warming scenario. The magnitude of projected warming is stronger than the ensemble mean of the GCMs due to the cold bias in their control simulation and may lead to reduction in the intensities of projected warming. $\text{RCM}_{\text{EM}}$ summer monsoon season has mixed precipitation projection like robust significant increase over peninsula (20%-40%) and Western Ghats and NE (10%-20%) by the end of 21st century. The noticeable point is that the forcing GCM suggests a decrease over
some parts of the peninsula whereas $RCM_{EM}$ suggest a robust significant increase over the same region. So $RCM_{EM}$ is altering the regional climate projections.

We have also prepared a tailored climate series for extreme temperature events over India. RCMs were able to simulate all the extreme temperature indices very well when compared to observations. Based on a threshold defined from the control simulation, the models have predicted that the warm days/nights/days may increase significantly toward the end of 21st century over India, whereas the cold days/nights are likely to be decrease significantly in the summer and the winter but in winter it not statically significant.

An ideal regional climate change scenario will be a scenario which has been developed from a chain of GCM-RCM simulations taking into account different emission scenarios, but for the present study only one scenarios results are used, in future we have plan to perform more scenario simulation for a robust conclusion.

There are many possibilities for extending this work to provide more information on the regional climate of India and how this could change in the future. Some current plans include:

- Extension to include other scenarios: An ideal regional climate change scenario will be a scenario which has been developed from a chain of GCM-RCM simulations taking into account different emission scenarios, but for the present study only one scenario is used, in future there are plans to extend this study to include other scenarios to provide a robust conclusion accounting for the uncertainty in future emissions.
- Atmosphere-ocean coupling: Sea surface temperatures have a strong influence on the climate of the region, so regional coupled models of the atmosphere-ocean could be more reliable than uncoupled ones.
• Land-use change: India is one of the rapidly developing regions of the world therefore land use change information is very necessary for the proper validation of the model.

• The northern boundary of the region is surrounded by Himalaya, which again has a strong influence on the climate of the region. Several large perennial rivers originate from this region as snow and glacier melts feeds them throughout the year. Including a glacier version of models such as REMO (for example including a glacier mass balance scheme) will enable models to properly simulate snow and glacier effect on regional climate as well as hydrological cycle of the region for their projections.

However, it is also expected that after having above modifications the results of the present study may not change much under present set-up. For example, in REMO, a new glacier scheme is introduced dynamically coupled with RCM. The REMO-Glacier simulation with ERAI and REMO HighNoon ERAI simulations, not much change is noticed (very preliminary results).

REFERENCES


Meteorological Department, NCC Research Report No.3.


Report No.9.


<table>
<thead>
<tr>
<th>Parameter</th>
<th>Data Set</th>
<th>Period</th>
<th>Resolution</th>
</tr>
</thead>
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<tr>
<td>Precipitation</td>
<td>IMD</td>
<td>1971-2005</td>
<td>0.5(^\circ) x 0.5(^\circ)</td>
</tr>
<tr>
<td></td>
<td>CRU</td>
<td>1901-2009</td>
<td>0.5(^\circ) x 0.5(^\circ)</td>
</tr>
<tr>
<td>2m Temperature</td>
<td>IMD</td>
<td>1970-2005</td>
<td>1(^\circ) x 1(^\circ)</td>
</tr>
<tr>
<td></td>
<td>CRU</td>
<td>1901-2009</td>
<td>0.5(^\circ) x 0.5(^\circ)</td>
</tr>
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<td>IMD</td>
<td>1970-2005</td>
<td>1(^\circ) x 1(^\circ)</td>
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<td>2m minimum temperature</td>
<td>IMD</td>
<td>1970-2005</td>
<td>1(^\circ) x 1(^\circ)</td>
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**Table-1:** List of all observed data sets used in this study.

<table>
<thead>
<tr>
<th>Description</th>
<th>Details</th>
</tr>
</thead>
<tbody>
<tr>
<td>Regional Models</td>
<td>REMO</td>
</tr>
<tr>
<td></td>
<td>Max Planck Institute for Meteorology, Hamburg, Germany</td>
</tr>
<tr>
<td>HadCM3</td>
<td>UK Met Office</td>
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<tr>
<td>CCLM</td>
<td>Gothe University, Frankfurt, Germany</td>
</tr>
<tr>
<td>Resolution</td>
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<tr>
<td>Domain</td>
<td>60.125 E to 100.125 E and 4.125 N to 40.125 N</td>
</tr>
<tr>
<td>Period</td>
<td>1960-2100</td>
</tr>
<tr>
<td>Forcing</td>
<td>ERA-Interim, ECHAM5-MPIOM, and HadCM3</td>
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<tr>
<td>Scenario</td>
<td>SRES A1B</td>
</tr>
</tbody>
</table>

**Table:** Details of RCMs simulations performed for the present study.
<table>
<thead>
<tr>
<th>Period</th>
<th>JJAS: Precipitation (mm/d)</th>
<th>Annual: 2m air Temperature (°C)</th>
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<tbody>
<tr>
<td></td>
<td>IMD</td>
<td>RCM_{REM}</td>
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<tr>
<td></td>
<td>Mean</td>
<td>SD</td>
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<tr>
<td>1901-1909</td>
<td>5.5</td>
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<td>1910-1919</td>
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<tr>
<td>1920-1929</td>
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<td>1930-1939</td>
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<td>1940-1949</td>
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<td>1950-1959</td>
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<td>1960-1969</td>
<td>5.8</td>
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<td>1979</td>
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<td>1980-1989</td>
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<td>1990-1999</td>
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<td>2000-2009</td>
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<td>2010-2019</td>
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<td>2020-2029</td>
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<td>2070-</td>
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### Table-3: Inter annual and decadal variability of observation and climate models of mean and standard deviation (red) of parameters precipitation (mm/d) and 2m air temperature (°C).

<table>
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<tr>
<th></th>
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<tbody>
<tr>
<td></td>
<td>Frequency</td>
<td>p-value</td>
<td>Frequency</td>
</tr>
</tbody>
</table>
Cold Nights | 4.464 | 0.1287 | 2.952 | 0.1164 | 2.928*** | 0
Cold Days  | 4.496* | 0.0811 | 1.952* | 0.0635 | 2.824*** | 0
Hot Nights  | 0.73 | 0.5359 | 2.824* | 0.0353 | 9.145*** | 0
Hot Days   | 2.525 | 0.9253 | 3.033 | 0.2535 | 13.646*** | 0
rx5day     | 4.086 | 0.1829 | 3.421** | 0.0224 | 2.151*** | 0

* Significant at 90%  ** Significant at 95%  *** Significant at 99%

Table 3: Annual mean frequency of the observations IMD and RCM ensemble mean extreme temperature and precipitation indices for the control and future climate. Unit is days/decade.
Figure-1: Climate models topography in meter. The higher horizontal resolution represents the better topography over south Asia. The lower panels shows the precipitation climatology (1970-1999, mm/d). IMD is observation.

Figure-2: Observed (CRU) temperature anomaly over India for the period 1901-2009, with respect to present day climate (normal: 1961-1990). The dark brown line shows the 11 year running mean.
Figure-3: Monsoon season precipitation climatology mean over India for (i) IMD, 1971-2005 (ii) CRU, 1901-2009 (iii) RCM ensemble mean of ERAI, 1989-2008 (iv) GCM ensemble mean, 1901-2099 (v) RCM ensemble mean, 1970-2099. The light/dark shaded region shows the spread of GCMs/RCMs used in the study. Unit is mm/d.
Figure-4: Same as Figure-3, for 2m air temperature. Unit is °C.
Figure-5: IPCC GCMs A1B scenario box-and-whisker plot for change in temperature (k) and precipitation (%) from 1970-1999 to (i) 2020-2049 (ii) from 2070-2099, over south Asia.
Figure-6: Spatial plots for $GCM_{FEM}$ for change in precipitation (%) from 1970-1999 to (i) 2020-2049 (ii) from 2070-2099, over south Asia. Lower panel show the temperature change (°C).
Figure 7: Spatial plots for RCM\textsubscript{EM} for change in precipitation (%) from 1970-1999 to (i) 2020-2049 (ii) from 2070-2099, over south Asia.

Figure 8: Spatial plots for RCM\textsubscript{EM} for change in temperature (°C) from 1970-1999 to (i)
2020-2049 (ii) from 2070-2099, over south Asia.

Figure-9: Trend and frequency of the extreme temperature and precipitation indices for the control and future climate over India.