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Focal Theme & Memorial Lecture

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Focal Theme: "Science & Technology for Climate Change Resilience & Adaptation"

Focal Theme & Memorial Lectures

Kerala State Council for Science, Technology and Environment
Sasthra Bhavan, Pattom, Thiruvananthapuram

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Focal Theme

KEY DRIVERS OF MONSOON VARIABILITY, TREND AND EXTREMES OVER KERALA

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Kerala, God's Own Country, has faced some devastating floods in recent years even as the mean seasonal rainfall has decreased. The drops in rainfall with increased extremes are consistent with monsoon changes at all India level. Kerala is however special because of its narrow coastal geography with the Western Ghats running through the state. Ocean controls rain over the West Coast of India unlike the Bay of Bengal where the atmospheric instabilities are the driver. Rapid and monotonic warming of the Indian Ocean, especially the Arabian Sea and the pull on the low-level south westerly jet by the Bay of Bengal convection and warming create a unique concoction for the foothills of the Western Ghats. Human perturbations on the Western Ghats convert heavy rains into manmade floods. Remote influences from the ocean warming pose challenges for adaptation and mitigation. But the good news is the improved short, medium and extended range and seasonal weather and climate forecasts can serve a Ready-Set-Go system for disaster management. Implementation of such a system is key for adaptive management of the food, water, energy systems and the continued vagaries of the monsoon over Kerala. The key drivers of the monsoon over Kerala will be discussed in this context variability, trend and extremes.

HYDROMETEOROLOGY IN CHANGING CLIMATE: COMPLEX PROCESSES AND ADAPTATION

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Changing characteristics of Indian Monsoon are evident from recent records of increasing droughts and floods. The society understands the need for climate adaptation and planning to increase climate resilience; however the number of studies is limited in this direction. One of the reasons behind this is the lack of interdisciplinary research that results into poor connection between science, policy and society. Indian monsoon is considered to be one of the most complex meteorological processes and models have their own limitations in simulating the same. Though models are performing well for large scale teleconnections such as relationship between El-Nino and monsoon; but still fail to incorporate local factors adequately. We show that a local factor plays a major role and makes the local scale rainfall processes more complex. As for example we find that land contributes quite significantly to the late monsoon rainfall. To examine the role of land surface hydrology in regional precipitation and to quantify recycled precipitation, the dynamic recycling model at a daily scale with NCEP Climate Forecast System Reanalysis (CFSR) data for the period of 1980–2010 is used. A high precipitation recycling ratio, that is, the ratio of recycled precipitation to total precipitation, is found at the end of the monsoon (September). As the monsoon progresses in India, enhanced soil moisture and vegetation cover lead to increased evapotranspiration and recycled precipitation. The recycling ratio is highest (around 25%) in north-eastern India, which has high vegetation cover leading to high evapotranspiration. Recycled precipitation over central and north-eastern India in September is responsible for delaying the withdrawal of the summer monsoon over these regions.
Global climate models including the Climate Forecast System version 2, the operational model used for prediction of Indian summer monsoon rainfall by the India Meteorological Department, has dry precipitation bias, mostly over densely populated Ganga basin. This restricts the use of model output in hydrological simulations/forecasts. We use regional atmospheric Weather Research and Forecasting model coupled with land surface models, driven by the boundary conditions from Climate Forecast System version 2. We find significant reduction in the dry bias of Indian summer monsoon rainfall with regional land-atmosphere model

and this attributes to (a) improved moisture transport from Western and Upper Indian Ocean to Ganga Basin and (b) improved precipitation recycling over the Ganga basin. We find that the smoothened topography in the global model allows advection of cold dry subtropical air into the Indian monsoon region, contributing to the cold temperature and dry precipitation bias. These results have important implications for monsoon simulations in developing operational hydro climatic prediction system in India.

There is an emerging understanding toward the importance of land-atmosphere interactions in the monsoon system, but the effects of specific land and water management practices remain unclear. Here, using regional process based experiments; we demonstrate that monsoon precipitation is sensitive to the choice of irrigation practices in South Asia. Experiments with realistic representation of unmanaged irrigation and paddy cultivation over north-northwest India exhibit an increase in the late season terrestrial monsoon precipitation and intensification of widespread extreme events over Central India, consistent with changes in observations. Such precipitation changes exhibit substantially different spatial patterns in experiments with a well-managed irrigation system, indicating that increase in unmanaged irrigation might be a factor driving the observed changes in the intraseasonal monsoon characteristics. Our findings stress the need for accurate representation of irrigation practices to improve the reliability of earth system modelling over South Asia.

Further to this there is also a need to use the present generation model outputs with their present skill and uncertainties in adaptation. Here we show two examples on the use of present generation models for irrigation water management and flood forecasting. We find that rather than generating chain of models by using one output to another, it is better to understand the local problem and generate solution that not only consider the climate science but also local information such as land, geomorphology, socio-economic information. Here we show two applications, irrigation water management at farm scale and extreme rainfall forecasting.

An efficient irrigation water management involves minimization of water loss avoiding any crop water stress. This remains a challenging task considering the uncertainty in the hydro-meteorological variables such as precipitation, temperature, humidity, wind velocity, soil moisture etc. and farm scale complex hydrological processes. Standard approach of agricultural water management (in practice only at a very few places) involves simple calculation of mass balance of water with a bucket model using monitored soil moisture. Sometimes they are aided by weather forecast; however, studies are limited on linking weather forecasts to water management. Few available studies either use crop specific empirical equations or use of mesoscale land surface model. None of them are really useful for a farm scale crop-water management. Further to this, the skill of weather forecasts has never been taken into account into these models for irrigation water management. Considering this, our proposed algorithm is a major breakthrough in the ground of precise agriculture, as it incorporates the skill of weather forecast (for 1 day/ 3 days/ 7 days) with its uncertainties in a probabilistic framework and connects to a farm scale eco-hydrological model. Farm scale equations and models are implemented to ascertain the hydrological processes which are involved in governing the pattern of soil moisture, which is more complex than a bucket model. This is further used inside an optimization model in an innovative way, where the probabilistic nature of the system is taken into account through Monte-Carlo simulations. The decisions related to water applications may be obtained corresponding to different level of reliabilities of avoiding crop water stress. Such an approach for farm scale management is unique and very useful for the regions/ states/ countries, which are already water stressed but the economy is driven by agriculture.

One of the widely used non-structural measures to mitigate flood is the use of weather forecast and alert generation. However, such methods limit only to the generation of rainfall forecasts that too associated with high false alarms and uncertainties. Though there has been a significant improvement in the skill of weather forecast models, still the forecasts are associated with high spatio-temporal bias. The state of art weather forecasting approach also does not consider the information related exposure and vulnerability. Here we introduce the concept of event specific risk at weather scale that considers the skill of forecast at a local scale along with regional information related to the exposure in terms of land use land cover, the geomorphologic vulnerability and the socio-economic vulnerability. The methodology is unique and novel as the concept of risk in terms of the product of hazard, vulnerability and exposure has never been used at weather scale and never been incorporated in real time flood forecasting system. The hazard is calculated on real time as the probability of getting an extreme rainfall (above 99th percentile) given a forecast. The probability is calculated from the hind cast (forecasts for observed period) and takes care of hit rate, false alarms and uncertainties. Vulnerability is defined as the sum of the socio-economic vulnerability and geomorphologic vulnerability. The exposure is calculated with respect to the land use and land cover. The methodology is applicable at weather scale (within

7 days) as well at extended range scale (2-3 weeks lead time) and can be used to identify the high risk zones well in advance, so that prevention, emergency response and evacuation can be done in time, and thus the loss can be minimized.

SCIENCE & TECHNOLOGY FOR CLIMATE CHANGE RESILIENCE & ADAPTATION

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This talk would mainly focus on (i) some basics of climate adaptation with brief introduction to principles and types of adaptation (ii) the need and rationale for adaptation actions, role of science and technology, the enabling factors and barriers in applying science & technology based solutions, providing key examples from different sectors and geographies.

As the aggregation of greenhouse gas emissions in the atmosphere take a toll on the climate, adaptation has become inevitable to protect the lives and livelihoods of vulnerable people. Adaptation is largely construed to be an adjustment process to combat the adverse effects of climate change at the local level. The ability to adapt is largely determined by the availability of capacities, information and knowledge, financial resources and application of appropriate technology. Most methods of adaptation involve some form of technology – which in the broadest sense includes not just materials or equipment but also diverse forms of knowledge. Adaptation is not a new phenomenon. Humans have adapted to changes induced by climate over years. There is a repository of knowledge on local adaptation measures that are time tested and practiced across geographies. Therefore, it is imperative to blend the traditional technologies with the emerging science-based adaptation solutions to manage climate risks effectively.

Adaptation science is an evolving area and the biggest challenges lies in identifying, designing and deploying the most appropriate adaptation technology and ensures that they serve those in greatest needs – the developing countries and the most vulnerable communities in a cost-effective manner. Technology can make an important contribution to climate adaptation, provided they are implemented in an enabling economic, institutional, legal, and socio-cultural environment. Climate adaptation is not a one-off activity, but a participatory process. It comprises more than the deployment of some hardware; it also includes considering soft technologies and non-technological options to complement and facilitate the use of technology. The technological solutions have to be boosted by political and social actions to bring transformative changes to address climate risks.

Memorial Lectures

Shri. P. T. Bhaskara Panicker Memorial Lecture

Climate Change Mitigation and Adaptation Technology Needs for India in Fulfilling International Commitments

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Scientist F & Head Technology Vision 2035Exercise TIFAC, Dept. of Science & Technology

I am deeply honoured to deliver the Shri P. T. Bhaskara Panicker Memorial Lecture who was not only a famous social activist but also a prolific science communicator of Kerala. I am really thankful to the organiser specially Dr. K. P.Sudheer, Executive Vice President of Kerala State Council for Science, Technology and Environment for giving me the opportunity to deliver this prestigious lecture. I congratulate KSCSTE for selecting the Climate Change theme for this congress which is very contextual as it is being discussed in almost all global forums.

We all know that entire globe is concerned about climate change and its impact. The impacts of climate change are devastating and unfortunately it hits most to the bottom of the pyramid sections of our society. Therefore, a fool proof climate change mitigation and adaptation actions are required for every nation to take on.

India, a huge country with a population of 1.3 billion where a significant number of population live in poverty, face severe challenges of balancing economic growth with sustainable development. It is a geographically diverse country with social and economic deprivations being witnessed in its vast rural areas. According to Global Climate Risk Index 2018, India ranks sixth as the most vulnerable country in terms of the impact of extreme weather events which is causing losses to the tune of about USD 9 to 10 billion annually.

Despite these obstacles, India has been achieving a progressive step towards reduction of emissions through various ways. India has always been a country where people have deep connection with their natural environment and surroundings. Throughout the ages people are dependent on natural resources for their livelihood and hold great reverence for Mother Nature. Indians have been utilizing minimum resources so as not to disturb the sanctity of natural environment, hence preserve the resources for our future population. This approach forms the fundamental aspect of the sustainability concept. The contribution of India to global emission is much less in compared to the developed nations. However, India has always taken a pro-environment approach since historical times and thus has a moral integrity to fulfil its part in contributing to the global fight on climate change.

Now let me brief about how climate change issues are dealt globally. United Nations Framework Convention on Climate Change (UNFCCC) is an international environmental treaty adopted on 9 May 1992 and entered into force on 21 March 1994, after a sufficient number of countries had ratified it. The prime objective of UNFCCC is to stabilize GHG concentrations in the atmosphere. UNFCCC has different categories of membership ie. Annex I Party (Developed Nations & Nations with Economies in Transition, Annex II Party (OECD members of Annex I, but not the EIT Parties), Non Annex I Party (Developing countries like India, China etc.) and Least Developed Countries (LDC). So far UNFCCC has 197 member parties.

The parties to the convention have been meeting annually since 1995 in Conferences of the Parties (COP) to discuss the actions taken by each party nation on climate change mitigation and adaptation purposes. Intervention from UNFCCC was voluntary in nature, however, in the Kyoto Protocol in 1997, a legally binding obligations for developed countries was devised to reduce their greenhouse gas emissions during the period 2008–2012.

So far top down approaches were taken in Conference of Parties, GHG emission reductions targets were set up in UNGCCC conferences and parties were supposed to adopt that. But this approach did not yield significant result. Therefore, in the Paris convention (COP 21) bottom up approach was adopted. Every country made their own commitments in Nationally Determined Contributions (NDCs) for governing emission reductions w.e.f. 2020 based on their capability (finance, technology competence, resource availability, implementation potential etc.) with a broader target lowering the temperature to 1.5 °C. The Paris Agreement entered into force on 4th November 2016.

Reporting mechanism about the Climate Change mitigation and adaptation actions to UNFCCC is different for different member groups. Being a Non-Annex I party to the Convention, India like many other developing nations, have to fulfil its reporting obligation to UNFCCC by submitting National Communications every four year and furnishing Biennial Updated Report (BUR) every two years, primarily to intimate their climate mitigation efforts. India is very particular in timely reporting to UNFCCC. India submitted its first National Communication in 2004 and second National Communication in 2012 though little delay but better than many other nations who even not submitted their first National Communication.

India submitted its first Biennial Updated Report (BUR I) in 2016 and second one (BUR II) on 31st December 2018 to the UNFCCC, which builds upon the information presented in the Second National Communication (SNC). Biennial reporting is mainly aimed at highlighting trends in the national greenhouse gas inventory, actions taken on climate change mitigation and adaptation, needs for climate friendly technologies, finance and capacity building.

As par Paris accord, India submitted its Intended Nationally Determined Contribution (INDC) in 2015 which was signed and ratified on 2nd October 2016 by Hon'ble Prime Minister of India and became Nationally Determined Contribution (NDC). India's national climate action plans as enumerated in its NDC, set three major quantitative targets: (a) reduce the Greenhouse Gas (GHG) emissions intensity of its Gross Domestic Product (GDP) by 33–35% of 2005 levels, by 2030; (b) build 40% of fossil-free power generation capacity by 2030, and (c) create an additional carbon sink of 2.5 to 3 billion tonnes of carbon dioxide equivalent (CO_2e) by 2030. India's ratification to NDC is a bold step, strengthened India's commitment to sustainable development and carbon emission reduction endeavor. Though there could be several hurdles ahead in fulfilling these commitments, yet they are achievable with adoption of climate friendly technologies along with conducive policies and robust implementation mechanism. Broad strategies in addressing these targets are:

- Adoption of Clean & Efficient Energy system
- Enhancing energy efficiency in industries
- Developing climate resilient urban centers
- Promoting waste to wealth conversion
- Safe, smart and sustainable green transport
- Planned afforestation
- Abatement of pollution\

Technology will play a key role in implementing all the above strategies. Technology development is dynamic in nature, hence identifying state-of-the-art technologies in achieving the NDC targets across sectors of national importance is need of the hour. Towards this, TIFAC with support from MOEF&CC, identified several technologies available globally in the sectors relevant in fulfilling India's commitment by using multiple technology foresight techniques viz. Literature survey, Horizon Scanning, Patent Analysis, Expert Consultations etc. Technologies thus identified were prioritized considering India's capabilities and constraints using Multi Criteria Decision Analysis (MCDA). Primarily, in MCDA process, technologies are screened through five broad parameters viz. Social, Technological, Environmental, Economic and Policy (STEEP) and accordingly, technologies which are suitable to Indian context were selected.

While mapping technology needs with NDC commitments, sectors comprising of Coal and Energy, Renewable, Transport, Waste, Industrial Processes and Product Use (IPPU) and Forestry were primarily considered. An array of technologies was identified that need to be transferred from other countries. These technologies have demonstrated remarkable success internationally and could have far reaching impacts when deployed locally. A handful of them have already been adopted, but the scale and speed of deployment need to be accelerated for realizing the goals of the Paris Agreement and the Sustainable Development Goals.

To further elaborate, technologies like Ultra Supercritical (USC) /Advanced Ultra Supercritical (AUSC) technology for coal plants and Underground Coal Gasification Technology (UCG) are deemed to increase efficiency for the coal and energy sector. Whereas Solar PV, CSP, Silicon based technologies look highly promising for renewables. Low temperature combustion, hydrogen fuel cells, hybrid engine technology for the transport sector seems to be promising for mitigating emissions. Likewise, biogas to bio-CNG and waste to energy technologies are identified in the waste sector. Similarly, energy and resource use efficiency technologies are the main focus for the IPPU sector. Within the forestry sector, intelligent nutrient management, simplified clonal technologies, models to control forest fires are few of the significant technologies. For adaptation sectors, a combination of technologies such as solar-powered farm machine and multi-stress resistant crop

varieties in agriculture sector, energy efficient production of bricks and carbon nano-tubes (replacing steel) for habitat sector, desalination technologies and aquifer recharge techniques within the water sector.
TIFAC has also identified few agenda for technology innovation as below which need immediate attention of research communities in order to take lead in technology development and deployment.

1. Fossil fuel free energy generation system
2. Fusion fission hybrid reactor
3. Advanced fossil fuel extraction technologies
4. Solar panels that moves like sunflower
5. Artificial lighting by using absorbed energy
6. Self-healing road
7. Eco-friendly waste management
8. Understanding national climate patterns and adapting to them
9. Manufacturing technologies that are not energy or manpower intensive
10. In situ purification water purification in pipeline
11. Development of easily detectable markers that help early detection of diseases
12. Sensor and protective devices to prevent spread of pandemics and epidemics
13. Development of nitrogen fixation property in cereals
14. Agriculture with minimal soil and water like vertical agriculture
15. Artificial Trees

Progress made so far with respect to NDC Commitment: As reported in BUR II report, submitted by India to UNFCCC on 31st December 2018, the emission intensity of Gross Domestic Products (GDP) has reduced by 21% over the period 2005-2014 as a result of India's proactive and sustained actions on climate change mitigation.Solar installed capacity in India has increased by about 9 times from 2.63 Gigawatt (GW) to 23.02 GW between March 2014 and August 2018.The installed capacity from non-fossil sources in electricity generation has increased from 30.5% in March 2015 to 35.5% in June 2018. Forest and tree cover increased from 24.01% of the total geographical area as reported in India State of Forest Report (ISFR) 2013 to 24.39% as reported in ISFR 2017.
Key Recommendations: Let me end my talk with the followings recommendations for the policy makers to push our country towards a low carbon economy, attaining climate change goals and targets and for further technology negotiation in international forum:

- Technology transfer mechanism from abroad need to be developed. IPR protection issues also need to be addressed.
- To create an enabling ecosystem for fostering innovations that would help in making India a sustainable climate change resilient Nation.
- To create a platform for conducting collaborative R&D globally towards addressing specific problems in the context of climate change with a defined role by the partnering institutes.
- Opportunities need to be explored for setting-up demonstration plants of select technologies that are highly relevant for the country's climate change context and also require colossal viability gap funding. In such cases, international funds such as Green Climate Fund (GCF) and Global Environmental Fund (GEF) may be explored.
- Development of India specific, indigenous climate change models to understand the impact of climate change on natural resources.
- To strengthen capacity building network in carrying out R&D and successful demonstration and implementation of climate change technologies throughout the country.

Dr. P. K. Gopalakrishnan Memorial Lecture

Technological Disruption of the Labour Market, What is the Empirical Evidence for India's Manufacturing Sector?

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Abstract: Anxiety about the prospect of technology displacing jobs on a large scale is currently dominating academic and public debate. A number of different occupations are likely to see an increased rate of automation in the near future. However, while studies have shown that this is likely to have an adverse effect on employment, they have all used the occupation-based approach to arrive at their conclusions. A task-based approach is used to arrive at a more accurate estimate of the effect of automation on manufacturing employment in India. Employing a comprehensive dataset from the International Federation of Robotics, the nature and extent of diffusion of industrial robots into the manufacturing industry in India is also analysed.

Keywords: Industrial automation, Robots, Employment, Technological change, India

The initiation of the Make in India programme is an indicator of the current Indian government's desire to increase employment in the country through the manufacturing route. Under this programme, the manufacturing sector is expected to contribute to at least a quarter of India's gross domestic product (GDP) by 2020. However, due to the capital-intensive nature of manufacturing,employment generated by the sector so far has been minimal. The pessimism surrounding this issue has been accentuated by the increasing amount of automation in manufacturing processes elsewhere in the world. Industrial automation is thought to have a deleterious effect on the creation of employment in different sectors of the economy, manufacturing included. This has given rise to an important debate, primarily in the context of developed countries where industrial automation has diffused manifold over a long period of time. This debate, which began in the popular press, has now been brought to the formal academic table by the publication of an influential and highly-cited piece of research by Frey and Osborne (2013). Subsequently, the *Journal of Economic Perspectives* organised a symposium on "automation and labour markets" in its summer 2015 issue.[1]In the wake of the symposium, a series of studies by academic economists and multilateral institutions, such as the Organisation for Economic Cooperation and Development, have also been published (Acemoglou and Restrepo 2017; Autor 2015; Brynjolfsson and McAfee 2014; Chang et al 2016; Hallward-Driemeier and Nayyar 2018).

Given this context, this article seeks to understand the extent of diffusion of automation technologies in Indian manufacturing and analyse its effects on employment in the sector.

The article is structured as follows. The first section discusses the concept of automation and identifies the specific automation technology that we consider in the present study. This is followed by a discussion of the motivation for the present study and the significance of the issues being dealt with. The next section delineates the major research questions raised, the methodology adopted to answer them, and the data sources employed. The section that follows engages with existing literature on the diffusion of automation technologies in manufacturing. The next section reports the main findings of our analysis with respect to Indian manufacturing. Finally, the implications of future developments in automation technologies on the conclusions reached in the previous section are discussed.

Understanding the Concept of Automation

Industrial automation involves a range of hardware and software technologies. The employment implications of these automation technologies vary considerably. The specific automation technology that has the most direct impact on employment is the multipurpose industrial robot. The International Federation of Robotics (IFR) defines an industrial robot as "an automatically controlled, reprogrammable, and multipurpose [machine]" (IFR 2014). In other words, industrial robots are fully autonomous machines that can be programmed to perform manual tasks such as welding, painting, assembling, handling materials, or packaging. Unlike other automation technologies, such as machine tools, programmable controllers, or computer-aided design equipment, industrial robots do not require human operators. They can perform reliably and consistently in harsh and constrained environments in which a human worker cannot function satisfactorily. Therefore, robots represent the most advanced and flexible form of industrial automation that can be envisioned. So, in the present study, we focus on industrial robots. In addition to industrial robots there are service robots as well. There are two conceptions of industrial robots: delivered (flow) and operational stock (stock). Since we are interested in employment implications, our primary focus is on operational stock of multipurpose industrial robots in the manufacturing sector in India, as this should give us a more accurate picture on employment implications.

Significance of the Study

In recent years, there has been a revival of concerns that automation and digitisation might result in a future with fewer and fewer jobs. These fears have been fuelled by studies from the United States and Europe which have argued that a substantial share of jobs is at "risk of computerisation." Adopting the occupation-based approach proposed by Frey and Osborne (2013), these studies assume that whole occupations rather than single job-tasks are automated by technology. This article argues that this approach might lead to an over-estimation of job automatability, as occupations categorised as high-risk often involve a substantial amount of tasks that are hard to automate.

In the Indian context, understanding the relationship between automation and employment is essential for the following reasons:

- Globally, fears about the effect of automation on employment are increasing. An extension of the earlier Frey and Osborne (2013, 2017)study showed that a whopping 69 % of all jobs in India are considered automatable.
- Industries such as computers and electronic products, electrical equipment, appliances and components, and transportation equipment and machinery are the most prone to automation. In many countries, including India, these four industries—in particular the transportation equipment industry—have been emphasised heavily in industrialisation strategy.
- Automation potential is concentrated in countries with large populations or high wages. India, therefore, is a good candidate.
- Of late, India's economic policy has focused on raising employment by promoting the growth of the manufacturing industry, but there has been a steady decline in the labour intensity of manufacturing employment (Sen and Das, 2014).
- Within India, there is now a debate as to whether employment has really increased in recent times, especially after economic liberalisation. The term jobless growth has been used to refer to a situation where the employment elasticity of output has been shown to be declining (World Bank 2018).

The rate of diffusion of automation technologies is likely to increase in the manufacturing sector in the near future. The following factors highlight the significance of the study in this context:

- A country such as India, which has chosen to focus on manufacturing quite late in its development, can skip stages and start with the latest manufacturing technologies.
- Due to globalisation, there is increasing pressure on manufacturing companies to be more productive and internationally competitive. Therefore, the pressure to adopt productivity-enhancing technologies is much greater now than ever before. According to estimates by Boston Consulting Group (2015), use of robots can decrease labour costs by as much as 16%.
- With recent developments in artificial intelligence (AI) and machine learning, the variety of tasks that machines can do has seen a quantum jump. For instance, industrial robots are now much more intelligent and can perform a number of operations which they could not do earlier.
- The declining cost of automation and its increasing availability is another factor that can hasten the rate of diffusion of robots. According to Boston Consulting Group (2015), the average price of industrial robotic systems has declined from $182,000 in 2005 to $133,000 in 2014 (Sirkinet al 2015).

These issues motivate us to understand how automation is being used in Indian manufacturing and its actual and potential effects on employment in the sector.

Research Methodology and Data Sources

The study attempts to answer the following research questions. At what rate have automation technologies diffused into Indian manufacturing over the period since the liberalisation of India's economy? What effect has this diffusion had on manufacturing employment? What is the relationship between the rate of diffusion of automation and the intensity of manufacturing employment? What are the likely trends in this relationship in the years to come, when the size and composition of manufacturing is bound to increase and become more sophisticated?

In order to understand the diffusion of industrial robots into manufacturing, we adopted a task-based approach because an occupation may contain several tasks that are not prone to easy automation. Therefore, the task-based approach mayprovide us a more accurate picture of the diffusion of automation. We measure diffusion through the operational stock of industrial robots per unit of employment. This framework is based on the work of Arntz et al (2017).

The primary data source is *World Robotics*, an annual survey of robotics that covers 32 countries, including India. It presents industry-wise and country-wise annual and time series data on the number of delivered robots and the operational stock. It also offers data on the task-wise distribution of robots within occupations. When calculating operational stock, it is assumed that the average service life of a robot is 12 years and that there is an immediate withdrawal of the robots after the specified period. Where countries actually do surveys of robot stock or have their own routines for the calculation of operational stock, such as in Japan, the resulting data is used. The survey has been published since 2006, with the latest edition covering providing information up to 2016. It is based on consolidated data provided by industrial robot suppliers worldwide, which is collected by national robot associations and robot suppliers and then processed by IFR's statistical department. The data is internationally comparable and thus allows analysis of the distribution of robots worldwide and in individual regions and countries. Further, it provides data on the density of robots per unit of employment in the industrial sector and tasks within industries where these installations are available. For India, data on operational stock and shipments is available since 1999. Industry-specific data is available since 2006, while task-specific data is only available since 2011. The source of the data on employment that is used for computing the density of robots is not always mentioned. Data on manufacturing employment has been taken from the *Annual Survey of Industries*, which offers industry-wise data up to and including the fiscal year 2014–15.

Engaging with Literature on Automation and Employment

The literature on the effect of automation on employment in manufacturing is a subset of the larger discussion about the effect of technological development on employment creation. This literature has developed in two phases. The first phase began in the late 1980s, when the first of the internationalstudies on the effect of industrial automation on employment was completed (Flamm 1988). The second phase began in 2013 with the publication of the Frey and Osborne (2013)study. The publication of this study unleashed a wave of concern about the deleterious effect of faster diffusion of automation technologies on employment in manufacturing. In turn, this has spawned a number of studies analysing the effects of automation on employment. These studies can be divided into three sets: the first set of studies analyses the diffusion of industrial robots in a range of countries, the second set shows an inverse relationship between the extent of diffusion of automation and employment in manufacturing, and the third set shows that increased automation has not really resulted in hefty job losses. In the following section, we review these studies at length.

Diffusion into Developed Countries: One of the earliest studies on the changing patterns of industrial robot use is the one by Flamm (1988). He analysed the rate of diffusion of robot use in Belgium, France, Germany, Italy, Japan, Sweden, the UK, and the United States between 1970 and 1984. His survey focused on two issues: how and where industrial robots were being used in manufacturing and how robot use in the United States compared with manufacturing practices abroad. Robot use is uneven across industries, with their use being confined to or concentrated in certain specific tasks and industries. Historically, they were first used—in relatively small numbers—in hazardous and unpleasant operations associated with metal processing. After

1975, Japanese auto manufacturers began to use them in large numbers in spot welding operations on their assembly lines. Later in that decade, they expanded the field of application to arc welding. Their foreign competitors followed suit. In fact, it was welding activities that hastened the diffusion of industrial robots across the developed world. After 1980, more sophisticated industrial robots began to be used in the electrical and electronics industries, with Japanese manufacturers at the forefront again. According to Flamm (1988), the majority of industrial robots are found in electronics assembly and automotive welding. The use of robots has not diffused further because there are only a handful of major use cases in which they are currently a cost-effective solution to manufacturers. In fact, industrial robot use has not increased consistently, but in fits and starts. In this context, Flamm is of the opinion that "one would be well advised to be sceptical of technological optimists who, on the basis of broad statistical job classifications for industrial workers, project veritable tidal waves of robots inundating manufacturing in the medium term".

Another interesting finding is that the diffusion of robot use has lagged in US manufacturing compared to Japan, Sweden, and Germany. Global variations in the relative prices of capital, labour, and other factors of production do not seem to explain the differential rate of diffusion. The shift to more product varieties that require more flexible manufacturing plants may be a more plausible explanation.

Inverse Relationship between Automation and Employment: The World Economic Forum (WEF 2016) conducted a large-scale survey of major global employers across 15 major developed and developing nations—which included the 100 largest global employers in each of the WEF's main industry sectors—to estimate the expected level of changes in job families between 2015 and 2020 and extrapolate the number of jobs gained or lost. It found that automation and technological advancements could lead to the loss of more than 5.1 million jobs due to disruptive labour market changes between 2015 and 2020 (WEF 2016). A total of 7.1 million jobs are expected to be lost—two-thirds of which are concentrated in the office and administrative job family—while a total of 2 million jobs will be added.

The McKinsey Global Institute (2017) conducted a similar survey covering 46 countries which account for about 80% of the global labour force. The study showed that almost half of all work activities can potentially be automated using current technology. Technically speaking, automatable activities touch 1.2 billion workers and $1,404 trillion in wages. China, India, and the United States account for over half of the automatable jobs. The study also notes that automation could boost global productivity by 0.8% to 1.4% annually.

A more systematic study of the diffusion of robots in US manufacturing was conducted by Acemoglu and Restrepo (2017). It analysed the impact of robot use on the US labour market between 1990 and 2007. Using a model in which robots compete against human labour to perform certain tasks, they showed that the local labour market effects of robots can be estimated by regressing the change in employment and wages on the exposure to robots in each local labour market based on the national penetration of robots into each industry and the local distribution of employment across industries. Using this approach, they estimated large and robust negative effects on employment and wages across commuting zonesresulting from robot use. They supplemented this evidence by showing that the commuting zones most exposed to robots in the post-1990 era did not exhibit any differential trends before 1990. The impact of robots is distinct from the impact of imports from China and Mexico, the decline of routine jobs, offshoring, other types of IT capital, and total capital stock (in fact, exposure to robots is only weakly correlated with these other variables). According to their estimates, one more robot per thousand workers reduces the employment to population ratio by 0.18–0.34 percentage points and wages by 0.25%–0.5%.

Occupation-based vs Task-based Approach: The main problem with these studies is that they consider very broad occupations and not tasks within occupations. In short, they follow the occupation-based approach of Frey and Osborne (2013). Very often, the assumption that whole occupations can be automated by technology are invalid. Rather, it is typically only specific job-tasks that are prone to automation. This approach may lead to an overestimation of job automatability as occupations labeled as high-risk often still contain a substantial share of tasks that are hard to automate.

An important international study that used a task-based approach was conducted by Arntzet al (2017). It concluded that automation and digitisation are unlikely to destroy large numbers of jobs. However, low-skilled workers are likely to bear the brunt of the adjustment costs as the auomatibility of their jobs is higher compared to highly skilled workers. Therefore, the likely challenge for the future lies in coping with rising inequality and ensuring sufficient retraining, especially for low-skilled workers.

Graetz and Michaels (2017) conducted another study that used IFR data on robot adoption from 1993 to 2007 to analyse industrial robot use across 17 countries. Employing panel data on robot adoption within industries in those countries, and new instrumental variables that relied on the robots' comparative advantages in specific tasks, the study found that increased diffusion of robotic technology contributed approximately 0.37 percentage points to annual labour productivity growth. Simultaneously, it raised total factor productivity and wages while lowering output prices. Further, the estimates suggest that robots did not significantly reduce employment, although they did reduce low-skilled workers' employment share.
The following inferences can be drawn from the studies that we have reviewed here:

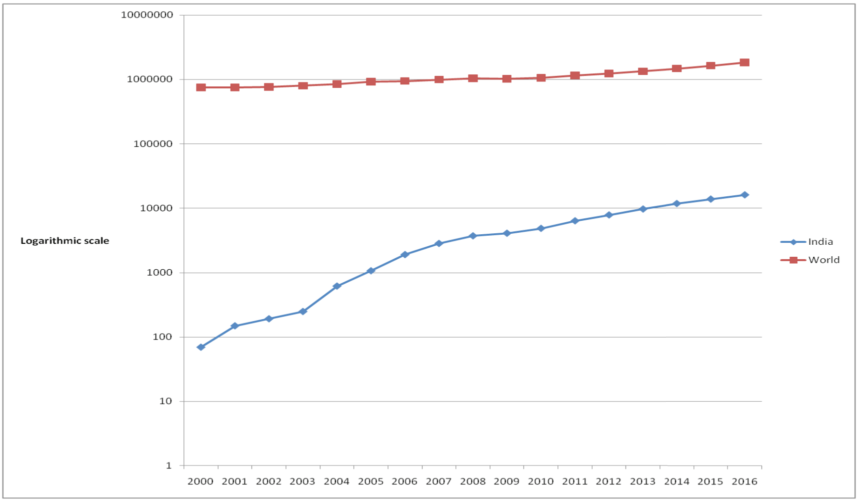
- Industrial robots are used in specific industries such as automobile, electrical and electronics, and metal working. Even within these industries, they are used only for certain tasks—like spot and arc welding—which are harsh on human beings and are highly repetitive tasks. In fact, their usage does not seem to have diffused into other manufacturing industries over the last four decades.
- Studies which have analysed the relationship between diffusion of automation and employment have got results which are diametrically opposite. Some studies have got an inverse relationship between the two variables, while others have not detected any such relationship. Careful analysis of the former studies shows that they have used an occupation-based approach while dealing with employment as opposed to a task-based approach. The occupation-based approach tends to exaggerate the impact of automation on employment.
- The proxy that is used for identifying automation has varied across studies. Some studies define automation in terms of computerisation, while others identify it in terms of use of industrial robots.
- All the studies—without exception—deal with developed market economies. None of them refer to any developing countries.

Thus, our engagement with the literature shows that there is a real need for a study analysing the relationship between automation and manufacturing employment in the context of a late-industrialising country such as India. Further, in our study, we define automation in terms of its highest form, namely the use of industrial robots. And we use a task-based approach to measure the effect of automation on employment, which should provide more meaningful results.

Main Findings for India

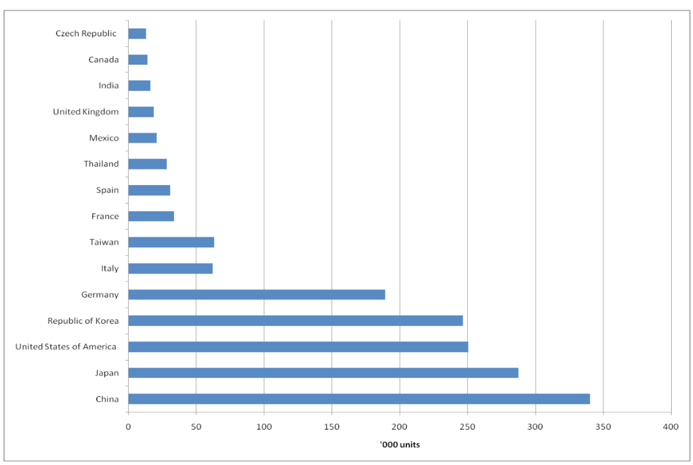
The operational stock of industrial robots in manufacturing has been increasing in India as well as globally. According to the IFR (2017), five major markets—China, Korea, the United States, and Germany—accounted for 74% of the total sales volume in the year 2016. China has become the largest market, representing almost a third of the total market in 2016. At a total of 87,000, the number of industrial robots sold in the country is almost equivalent to the total number of industrial robots sold in Europe and America together. Apart from China, the other important markets for industrial robots are Japan, the US, the Republic of Korea, and Germany (Figure 2). In India, operational stock increased from just 70 in 2000 to 16,026 in 2016—an annual growth rate of 44% (Figure 1). Industrial robot sales in India increased by 27% in 2016.

Figure 1: Operational Stock of Industrial Robots in the World and in India in 2016



Source: International Federation of Robotics (2017)

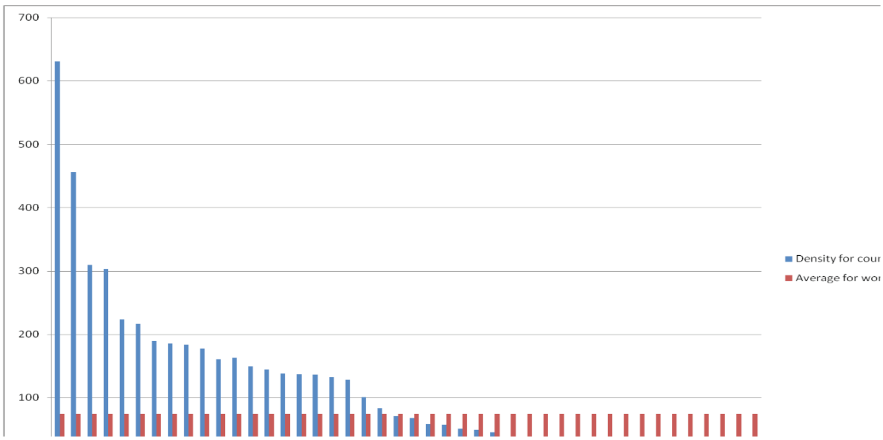
Figure 2: Estimated Operational Stock of Industrial Robots in 15 Largest Markets Worldwide in 2016



Source: International Federation of Robotics (2017)

Despite having the largest operational stock of robots, China was still below the world average in terms of robot density in 2016. India appears to have the lowest density, although this is the result of an underestimation which will be made clear in our own estimates of the density of industrial robots. The Republic of Korea has had the highest robot density in the world since 2010 (Figure 3). In 2016, the country had 631 industrial robots in operation per 10,000 employees—up from 311 units in 2010. The increase was due to the continued installation of large volumes of robots, particularly in the electrical and electronics industry and in the automotive industry. Singapore ranked second with 488 robots per 10,000 employees in 2016. The country's high robot density is down to the low number of employees in its manufacturing industry—approximately 240,000 according to the International Labour Organisation—and the large number of installed robots, which has increased significantly in recent years. About 90% of the robots in use in Singapore are installed in the electronics industry.

Figure 3: Density of Industrial Robots across Developed and Developing Countries in 2016 (per 10,000 employees)



Source: International Federation of Robotics (2017)

It will be instructive to analyse whether the industries where robots are used—and the robot-dependent tasks within these industries—have undergone any changes since Flamm (1988)made his observations in the late 1980s. Three industries account for about 80% of the entire operational stock of industrial robots: metal, electrical and electronics, and automotive (Table 1). Among these industries, the automotive industry accounts for about 43% of robot usage. In fact, it is the only industry which has increased its share over the years. Interestingly, the same industry accounted for the largest share in the 1980s as well (Flamm 1988). We shall now analyse the tasks or application areas within these industries where industrial robots are used (Table 2).

Table 1: Trends in Global Distribution of Operational Stock of Industrial Robots in the Metal, Electrical and Electronics, and Automotive Industries (percentage shares)

	Metal	Electrical and Electronics	Automotive	Total
1993	17.07	31.97	27.83	76.86
1994	17.16	31.63	27.76	76.55
1995	16.77	30.77	27.97	75.52
1996	16.25	30.20	28.74	75.20
1997	15.62	29.74	28.89	74.25
1998	14.75	28.95	29.84	73.53
1999	13.91	27.76	30.53	72.20
2000	12.90	26.83	31.47	71.20
2001	13.20	24.06	33.98	71.24
2002	12.96	22.24	35.96	71.17
2003	12.66	20.91	38.11	71.68

2004	11.87	20.04	40.95	72.86
2005	11.06	20.46	42.43	73.95
2006	11.36	19.02	44.59	74.98
2007	11.54	18.63	44.95	75.13
2008	12.16	18.23	44.90	75.30
2009	12.19	17.92	45.26	75.38
2010	11.97	18.78	45.92	76.67
2011	11.55	20.42	45.57	77.54
2012	11.28	21.51	45.44	78.23
2013	11.16	22.18	45.58	78.92
2014	11.21	22.48	45.76	79.45
2015	11.55	23.58	44.71	79.84
2016	11.46	25.77	43.21	80.43

Source: International Federation of Robotics (2017)

Table 2: Task-wise Distribution of Industrial Robots in Global Manufacturing 2011-2016 (percentage shares)

IFR Class	Application area	2011	2012	2013	2014	2015	2016
110	**Handling operations/Machine tending**	**41.3**	**44.3**	**43.6**	**47.1**	**48.4**	**47.4**
111	Handling operations for metal casting	1.0	1.1	0.9	0.9	1.1	1.5
112	Handling operations for plastic moulding	6.9	7.5	6.9	8.1	8.4	6.9
113	Handling operations for stamping/forging/ bending	0.8	0.9	0.7	1.0	0.9	0.9
114	Handling operations at machine tools	3.9	4.4	5.6	4.2	5.6	5.1
115	Machine tending for other processes	1.9	1.5	1.4	1.0	1.6	0.9
116	Handling operations for measurement, inspection, testing	1.6	0.6	1.0	0.7	0.7	0.5
117	Handling operations for palletizing	2.8	3.3	3.2	3.3	3.9	3.5
118	Handling operations for packaging, picking and placing	7.5	9.7	7.2	12.2	10.7	10.0
119	Material handling n.e.c	15.0	15.2	16.7	15.6	15.3	18.0
120	Handling operations/machine tending unspecified						

160	**Welding and soldering (all materials)**	**28.9**	**28.4**	**28.0**	**26.2**	**23.9**	**22.1**
161	Arc welding	12.7	13.2	12.8	11.2	9.8	8.6
162	Spot welding	14.9	14.7	13.5	13.0	12.5	11.6
163	Laser welding	0.4	0.2	0.3	0.2	0.2	0.2
164	Other welding	0.5	0.2	1.2	0.9	0.6	0.7
165	Soldering	0.5	0.0	0.0	0.8	0.9	0.9
166	Welding and soldering unspecified						
170	**Dispensing**	**4.2**	**4.0**	**4.9**	**3.6**	**3.6**	**3.3**
171	Painting and enamelling	2.8	2.7	2.8	2.4	2.1	2.3
172	Application of adhesive, sealing material or similar material	0.9	1.0	1.2	0.4	0.6	0.3
179	Dispensing others/Spraying others	0.5	0.2	1.0	0.8	0.9	0.6
180	Dispensing unspecified						
190	**Processing**	**1.4**	**2.0**	**1.8**	**2.5**	**2.1**	**1.3**
191	Laser cutting	0.1	0.5	0.2	0.2	0.3	0.1
192	Water jet cutting	0.1	0.1	0.2	0.2	0.1	0.1
193	Mechanical cutting grinding/deburring/ milling/polishing	0.6	0.9	1.1	1.8	1.4	0.7
198	Other processing	0.6	0.5	0.3	0.3	0.3	0.3

Source: International Federation of Robotics (2017)

Industrial robots are primarily used in two main tasks: handling operations/machine tending, and welding and soldering. There is a remarkable continuity in the use of robots for certain tasks from the late 1980s to 2016. The only difference is that more of them are used for the same kind of tasks. The only task that has increased its share is material handling, which shows that industrial robots are primarily used for tasks that are difficult for human beings to perform.

Firms employ robots to automate specific tasks—many of them harmful to human health. The range of automatable tasks is continuously increasing and will continue to increase through advances in vision and end-effector technologies.[2] But this does not imply that jobs will be wiped out.

We now turn our attention to the Indian case. As mentioned earlier, the operational stock of industrial robots in India has seen a tremendous increase since 2000 (Figure 1). However, the rate of growth has been fluctuating (Table 3). The manufacturing sector's share has been rising steadily and now accounts for about two-thirds of the operational stock. It is also interesting to note that the number of robots being used in both construction and education/research and development has increased significantly. However, the industry-wise usage numbers are coloured by the large number of robots whose usage cannot be ascribed to any specific sector.

Table 3: Industry-wise Trends in Operational Stock of Industrial Robots in India

	All industries	Manufacturing	Electricity, gas and water suplly	Construction	Education R&D	Other manufacturing	Unspecified
1999	50	0	0	0	0	0	50
2000	70	0	0	0	0	0	70
2001	150	0	0	0	0	0	150
2002	193	0	0	0	0	0	193
2003	250	0	0	0	0	0	250
2004	619	0	0	0	0	0	619
2005	1069	0	0	0	0	0	1069
2006	1905	497	0	6	5	0	1397
2007	2833	799	0	14	8	0	2012
2008	3716	1201	0	15	8	0	2492
2009	4079	1302	0	16	10	0	2751
2010	4855	1517	0	16	11	0	3311
2011	6352	2189	0	17	17	1	4127
2012	7840	3526	1	18	23	1	4270
2013	9677	5189	1	27	40	1	4417
2014	11760	7138	1	29	53	1	4536
2015	13768	8953	1	30	62	1	4718
2016	16026	11237	1	30	82	1	4671

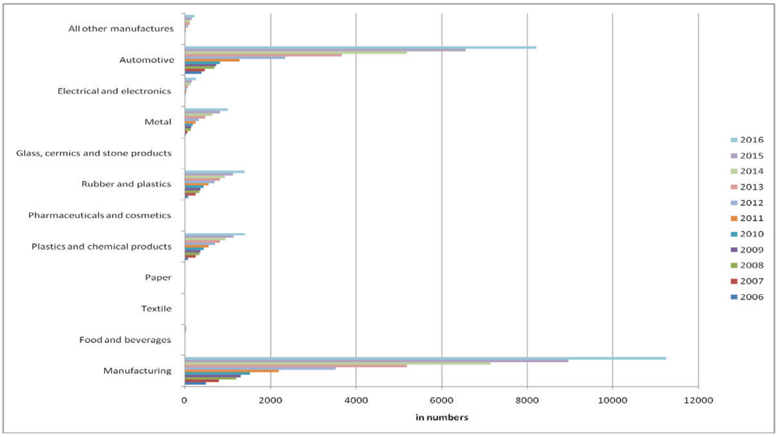
Source: International Federation of Robotics (2017)

Table 4: Industry-wise Trends in the Number of Delivered Robots in India

	All industries	Manufacturing	Electricity, gas and water supply	Construction	Education, R&D	Others no manufacturing	Unspecified.
1999	50	0	0	0	0	0	50
2000	20	0	0	0	0	0	20
2001	80	0	0	0	0	0	80
2002	43	0	0	0	0	0	43
2003	57	0	0	0	0	0	57
2004	369	0	0	0	0	0	369
2005	450	0	0	0	0	0	450
2006	836	497	0	6	5	0	328
2007	928	302	0	8	3	0	615
2008	883	402	0	1	0	0	480
2009	363	101	0	1	2	0	259
2010	776	215	0	0	1	0	560
2011	1547	672	0	1	6	1	866
2012	1508	1337	1	1	6	0	163
2013	1917	1663	0	9	17	0	227
2014	2126	1949	0	2	13	0	162
2015	2065	1815	0	0	0	0	250
2016	2627	2284	0	0	0	0	343

Source: International Federation of Robotics (2017).

Figure 4: Industry-wise operational stock of industrial robots in India, 2006–2016



Source: International Federation of Robotics (2017)

The manufacturing sector accounts for the lion's share of delivered robots in India(Table 4). However, within manufacturing, most of the robot installations are in four industries: automotive, electrical and electronics, metal, chemical, rubber and plastics. In 2017, there was a 27% increase in the number of delivered robots compared to the previous year. On average, the number has increased by 64% per annum during the period under consideration.

An analysis of the industry-wise operational stock of industrial robots shows that robot use is highest in the automotive industry, followed by plastics, rubber and chemicals, and metal. In short, it is the growth of the automotive industry that accounts for most of the growth in robot installations in India. Thus, the pattern in India is very similar to the international pattern.

Task-based installations: Robot usage in India is confined to two tasks, namely welding and soldering, and handling and machine tending (Table 5). Within the former, it is almost entirely concentrated in arc and spot welding. Material handling involving plastic moulding and machine tools accounts for the second largest share. This resembles the pattern observed historically even in developed countries.

This finding has deep implications for employment. Industrial robots have hitherto been used for tasks that are inhospitable for human labour and where a lot of precision is required. However, in order to understand the employment implications of robot use, one has to analyse the density of robots per unit of employment.

Table 5: Task-based Operational Stock of Industrial Robots in India (2011–2016)

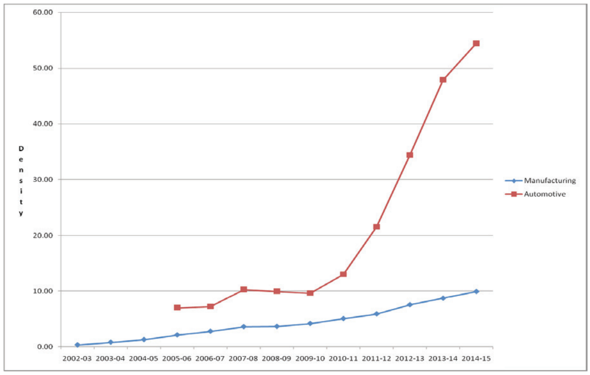
Table 5 : Task –based Operational Stock of Industrial Robots in India (2011 -2016)

Task	2011	2012	2013	2014	2015	2016	CAGR 2011-2016
Handling operations for machine tending	2,101	2,531	2,903	3,404	3,948	4,760	18%
Handling operations for metal casting	44	58	62	68	93	111	20%
Handling operations for plastic molding	38	676	790	905	1,097	1,387	21%
Handling operations for tamping ginning	78	91	100	109	117	158	15%
Handling operations at machine tools	390	440	472	519	622	789	15%
Machine tending process	42	48	51	51	51	51	4%
Handling operations for measurement inspection, testing	6	8	8	9	9	10	11%
Handling operations for palletizing	49	63	74	87	99	114	18%
Handling operations for picking and packing	29	47	63	65	78	90	25%
Material handling etc.	925	1,100	1,283	1,59	1,782	2,050	17%
Handling operations machine tending magnified							
Welding and soldering	2,720	3,561	4,775	6,095	7,324	8,800	26%
Arc welding	1,707	2,354	3,073	3,736	4,415	5,264	25%
Spot welding	938	1,125	1,602	2,250	2,780	3,380	29%
Laser welding	9	15	25	27	34	38	33%
Other welding	55	56	62	69	82	102	13%
Soldering	11	11	13	13	13	16	8%
Welding and Soldering							
Dispensing	640	776	982	1,127	1,286	1,392	17%
Painting and name ling	467	582	740	847	924	1,015	17%
Application of adhenvve materials or similar materials	136	155	190	219	231	233	11%
Dispensingoher/Sparingohers	37	39	52	61	131	144	31%
Dispense specified							
Processing	90	130	172	223	25	259	24%
Laser cutting	5	6	7	8	8	9	12%
Water jet cutting	5	7	7	9	11	16	26%
Mechanical cutting/polishing	21	37	73	109	117	133	45%
Other processing	59	80	85	97	99	101	11%
Processing specified							
Assembling and disassembling	71	93	139	184	261	366	39%
Fixing, press fitting	61	83	129	170	229	328	40%
Assembling	5	5	5	9	10	16	26%
Disassembling							
Others	5	5	5	5	22	22	34%
Clean roof FPD							
Clean room for conductors	113	129	147	206	240	271	19%
Clean room for	5	5	5	5	5	6	4%
Clean room for conductors							
Clean room for duties							
Others	108	124	142	201	235	265	20%
Unspecified	617	620	559	21	474	178	-22%
Total	6352	7,840	9,671	11,760	13,768	16,026	20%

Source: International Federation of Robotics

Density of Robots: The density of robots in India is one of the lowest among robot using countries (Table 6). Density is an important indicator of the labour-displacing effect of industrial robot use. Figure 5 provides estimates of robot density in two different industries: the manufacturing industry and the automotive industry. Although both industries are showing an increase in robot density, it is much higher in the automotive industry than the general manufacturing industry. Since the automotive industry in India is dominated by affiliates of multinational companies, with the parent companies having a long history of using industrial robots in various manufacturing operations, it is only natural that their affiliates in India will be using industrial robots (Table 7).

Figure 5: Trends in Industrial Robots Density in India, Manufacturing vs Automotive Industry



Source: International Federation of Robotics (2017) and Central Statistical Organization (2015)

Table 6: Extent of Diffusion of Automation Technologies in India Compared to other Countries (Density of Industrial Robots per 10,000 Employees)

Industry	India	China	Brazil	Thailand	Malaysia	Korea	Japan
Manufacturing	10	49	11	52	33	531	305
Automotive	54	392	125	859	281	1,218	1,216
All other industries	1	24	5	22	22	411	213

Source: International Federation of Robotics (2017)

Table 7: Industrial Robots usage in MNC Affiliates in India's Automotive Industry

Name of Company	Name of plant	Number of industrial Robots	Number of Employees	Density of robots
Ford Motor India	Sanand, Gujarat	453	2,500	1,812
Hyundai Motor India	Irungattukottai, Tamil Nadu	400	4,848	825
Volkswagen India	Chakan, Pune	123	2,000	615

Source: Company sources

The robot densities in these state-of-the-art plants are significantly higher than the average for the Indian automotive industry. Even domestic automotive manufacturers such as Tata Motors are deploying industrial robots, albeit at a lower density level. In a single plant in Pune, Tata is said to have installed 100 robots. According to the company, automation increased turnover by 250% despite the production force being reduced by 20% during the same period.

Highly labour-intensive industries such as paper and wood products, textiles, non-metallic products, food products, metal products, and machinery are the least automated. The most automated industries, such as automotives, rubber and petroleum, basic metals and chemicals, are less labour-intensive. So the effect of automation has an insignificant effect on the quantum of overall employment in the manufacturing industry.

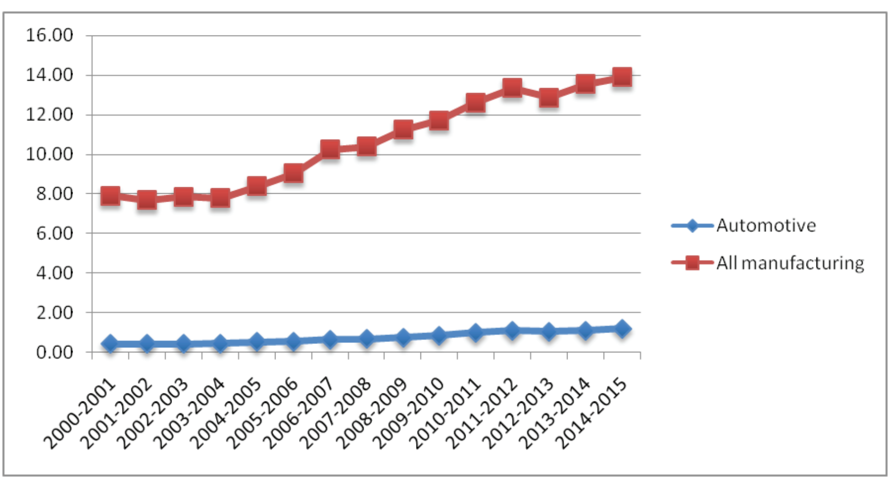
Production of Industrial Robots in India: Some of the world's leading firms in factory automation, such as Fanuc, Kuka, Gudel, and ABB, have manufacturing and sales operations in India. One of them has even established a training academy in Pune to train engineering graduates in robotics. These operations could hasten the diffusion of industrial robots in non-traditional industries. Further, TAL Manufacturing Solutions, a subsidiary of Tata Motors, has launched its much-awaited TAL Brabo robot. It comes in two variants with payloads of 2 kg and 10 kg each and is priced between ₹5,00,000–₹7,00,000. The robot was developed in-house with TAL Manufacturing doing the design and Tata Elxsi handling the styling and Tata AutoComp manufacturing some critical components of the robot. The TAL Brabo has apparently been developed to cater to micro, small, and medium enterprises, as well as for the use of large-scale manufacturers who require cost-competitive automated solutions in manufacturing. Conceptualised to complement a human workforce and perform dangerous, repetitive, high-volume, and time-consuming tasks, the robot can be deployed across industries. Having successfully tested the TAL Brabo in over 50 customer work streams, TAL Manufacturing is ready to supply these robots to several sectors including automotive, light engineering, precision machining, electronics, software testing, plastics, logistics, education, and aerospace.

Implications of Automation on Traditionally Labour-intensive Industries

One of the most labour-intensive industries in India is the cotton textile industry—especially readymade garments. The Sewbot technology, being developed by the American company Softwear Automation, aims to automate the entire clothes-making process. However, the technology is very highly-priced and its diffusion in the textile industry will take years to fructify. There are four processes that go into making an item of clothing: picking up the item, aligning it, sewing it, and disposing of it. Of these, only the sewing has so far been automated—by the sewing machine, which came in a long time ago. The other parts of the process are still done faster and cheaper by humans than by robots.

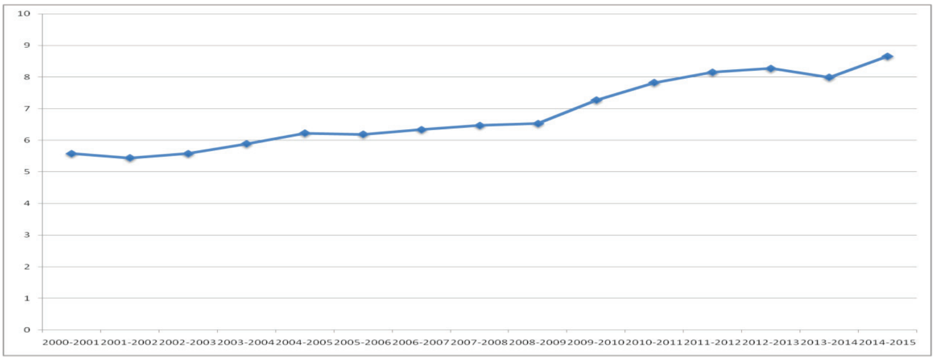
In fact, the most automated industry in India, the automotive industry, accounts for only about 10% of manufacturing employment in the country (Figure 6a, Figure 6b). We have already seen that even within this industry, only certain tasks are automated.

Figure 6a: Employment Trends in India's Automotive Manufacturing Industry



Source: Computed from Annual Survey of Industries

Figure 6b: Share of Automotive Sector Employment in Total Organised Manufacturing Sector Employment



Source: Computed from Annual Survey of Industries.

However, automation technologies are improving fast, with significant developments forthcoming in the areas of AI and machine learning—especially a technique known as deep reinforcement learning—and robotics. Further, improvements in the following eight technologies will have a strong positive effect on faster diffusion of automation technologies:

1. Computing performance
2. Electromechanical design tools and numerically-controlled manufacturing tools
3. Electrical energy storage
4. Electronics power efficiency
5. Local wireless digital communications
6. Internet
7. Data storage
8. Computation power

Another significant factor is China's increasing share of the robotics industry (Figure 7). China's tech industry is shifting away from copying Western companies and has identified AI and machine learning as the next big areas of innovation. Chinese investors are now investing heavily in AI-focused startups and by pledging to invest about $15 billion by 2018, the Chinese government has signalled its desire to see the country's AI industry blossom. The combination of these three factors could make industrial robots more intelligent and capable of performing tasks which were hitherto considered impossible. China's entry into robotics could make robots much cheaper and make them affordable even to newer industries. Faster adoption of these new automation technologies could have a deleterious effect on employment in Indian manufacturing—especially in labour-intensive industries such as textiles and clothing.

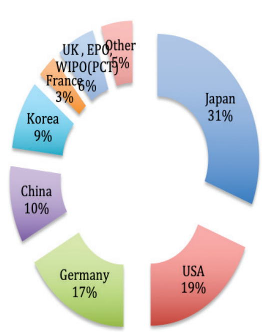


Figure 7: Country-wise Patents Granted in Robots and Autonomous Systems
Source: Intellectual Property Office (2014)

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In Conclusion

In this study, we have analysed the possible links between diffusion of automation technologies and employment. Automation technology is narrowly defined in terms of the highest form of automation—namely, the use of industrial robots—primarily because of the availability of reliable data on industrial robot use at the level of tasks within occupations. Analysis of the data shows that although robot density has increased, its usage is restricted to a few industries, with the automotive industry being the most important user. Within the automotive industry, the use of industrial robots is concentrated in certain tasks that are less labour-intensive. So, for the present, automation does not pose a threat to manufacturing employment. However, with rapid developments in technology, the situation could change. Therefore, there is a need for a policy on automation in an economy such as India's, wherein labour is abundant

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Dr. P. R. Pisharoty Memorial Lecture

Hydro-Meteorological Impacts of Climate Change

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Climate change presents a significant challenge for hydrologists and water resource engineers because of the large uncertainties associated with its likely impacts on water availability, water quality, frequency and magnitude of floods and droughts, coastal inundation and salinity intrusion. In this lecture, a discussion on climate change issues in water availability, floods, meteorological droughts and water quality at river basin scales, is provided. The cumulative effects of gradual changes in hydrology due to climatic change are expected to alter the magnitude and frequency of peak flows over the service life of flood control infrastructure. Potential future changes in rainfall intensity can alter the level of service of infrastructure, with increased rainfall intensity likely resulting in more frequent flooding. A rise in sea-levels can lead to coastal inundation and decreased drainage capacities. These observations however are burdened with uncertainties arising out of uncertainties in future climate projections.

A major research focus in hydrologic sciences in recent years has been assessment of impacts of climate change at regional scales. A commonly adopted methodology for assessing the regional hydrologic impacts of climate change is to use the climate projections provided by the General Circulation Models (GCMs) for specified emission scenarios in conjunction with the process-based hydrologic models to generate the corresponding hydrologic projections. The scaling problem arising because of the large spatial scales at which the GCMs operate compared to those required in distributed hydrologic models, is addressed by downscaling the GCM simulations to hydrologic scales. Projections obtained with this procedure are burdened with a large amount of uncertainty introduced by the GCMs and emission scenarios, small samples of historical data against which the models are calibrated, downscaling methods used and other sources. Quantification and reduction of such uncertainties is a current area of research in hydrology. This lecture provides an overview of the work done in this direction, with applications to Indian case studies and brings out issues of scientific interest.

Introduction

There is increasing scientific consensus based on currently available evidence that anthropogenic activities have changed atmospheric composition leading to an increase in mean global temperature, and alteration of meteorological processes that define climate (IPCC, 2007). Changes in weather patterns, increasing climate variability and anticipated increases in weather extremes are expected to affect hydrologic conditions and the hydrologic responses of watersheds. The quantification of the effects of climate change is primarily based on the results of computer simulations of General Circulation Models (GCMs) for various scenarios developed based upon a number of assumptions regarding the future discharge of greenhouse gasses into the atmosphere. While GCM performance with respect to global temperature is impressive, precipitation effects are less well simulated. There are serious inconsistencies between GCMs with respect to not only the magnitude of change, but in some cases also the direction. Direct outputs of precipitation from GCMs are not generally considered reliable, and hence there has been a considerable research effort to improve the estimation of precipitation under future climate by the development of dynamical and statistical downscaling methods.

In terms of impacts of climate change affecting normal human life, the biggest impact will be on water – with respect to both water availability and extremes of floods and droughts. Although with global scale projections, a possible increase in the mean precipitation over India is indicated, a considerable spatial variation in the regional precipitation patterns result in some regions within the country receiving lower rainfall in the future. The climate change has implications in terms of modifications in water availability, agricultural water demand, hydrologic extremes of floods and droughts, water quality, salinity intrusion in coastal aquifers, groundwater recharge and other related phenomena. Increase in atmospheric temperature, for example, is likely to have a direct impact on the river runoff in snow-fed rivers and on the evaporative demands of crops and vegetation apart from its indirect impacts on all other phenomena of interest in hydrology and water resource management. Similarly a change in the regional precipitation pattern could have direct implications on water availability, floods and droughts. Thus, climate change, in as much as it affects the common man, is indeed a change in the overall water scenario at a local scale. Climate change, in conjunction with other changes occurring in the country such as rapid urbanization and industrial growth has serious implications on the policy and infrastructural growth in the water and related sectors.

To understand the regional implications of climate change on water policy and infrastructure, it is necessary to first obtain regional projections of temperature, precipitation, streamflow and other variables of interest and then use these projections in the impact models to relate the projections to specific impacts. A commonly adopted methodology for assessing the regional hydrologic impacts of climate change is to use the climate projections provided by the General Circulation Models (GCMs) for specified greenhouse gas emission scenarios in conjunction with the process-based hydrologic models to generate the corresponding hydrologic projections. The scaling problem arising because of the large spatial scales at which the GCMs operate compared to those required in most distributed hydrologic models, is commonly addressed by downscaling the GCM simulations to smaller scales at which impacts are needed. Vulnerability assessment, adaptation and policy issues form the logical extensions to provide the water resources managers and infrastructure developers with options for adaptive responses.

In this lecture, climate change issues specifically related to water availability, water quality, urban floods and meteorological droughts are discussed.

Projections of Water Availability under Climate Change Scenarios

Figure 1 describes the general procedure used to assess the climate change impacts on water resources at river basin scales. The climate projections for pre-specified scenarios of greenhouse gas emissions in the atmosphere are obtained from the General Circulation Models (GCMs). The projections are next brought down to the spatial scales of interest. For example, if we are interested in precipitation at a sub-division scale, the projections on climate variables influencing the precipitation, provided by the GCMs – which are at scales typically of the order of about 250 km by 250 km – are 'downscaled' to the sub-division scales and used in obtaining the projections for future precipitation. The projections are used as inputs to run hydrologic models that are calibrated with the historical observed hydrologic variables (e.g., streamflow, evapotranspiration, soil moisture etc.). Other inputs used relate to the land use patterns, soil type, and catchment characteristics etc., which are not likely to be influenced by climate change. This step of running the hydrologic models with future projected variables influenced by climate change produces the projections of streamflow and other variables of interest, and provides an estimate of how the future streamflow is likely to be in comparison with the historical flows and thus quantifying the water availability in the river basin in the future, under climate change scenarios. Time windows used for such assessment may be, typically, the years 2020s, and 2040s. These assessments may be used in long term planning and infrastructural decisions.

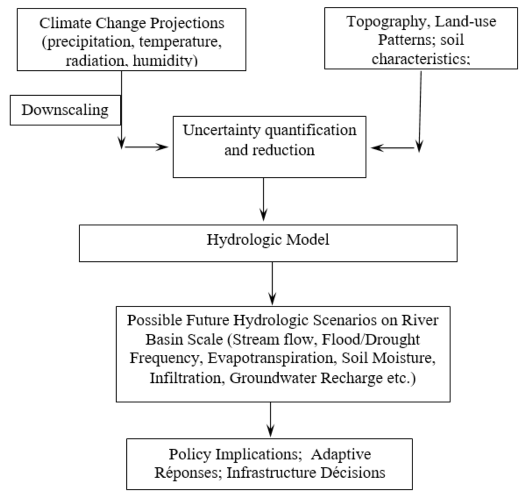
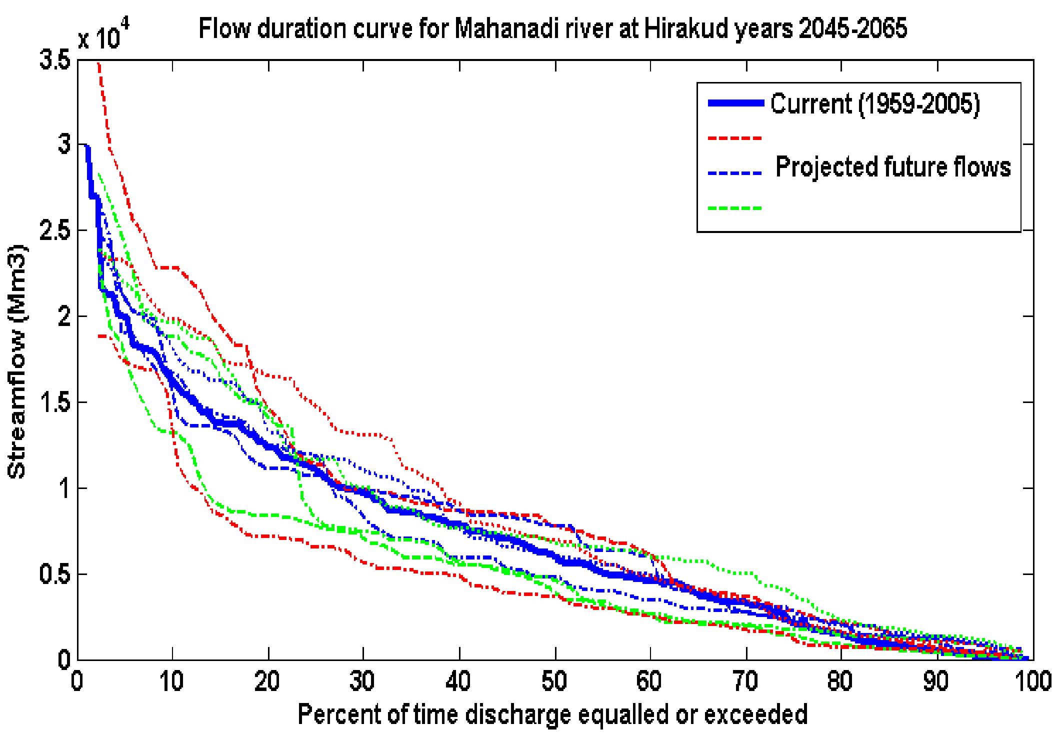


Figure 1. Block diagram showing the procedure used in climate change impact assessment (Source: Mujumdar, 2011)



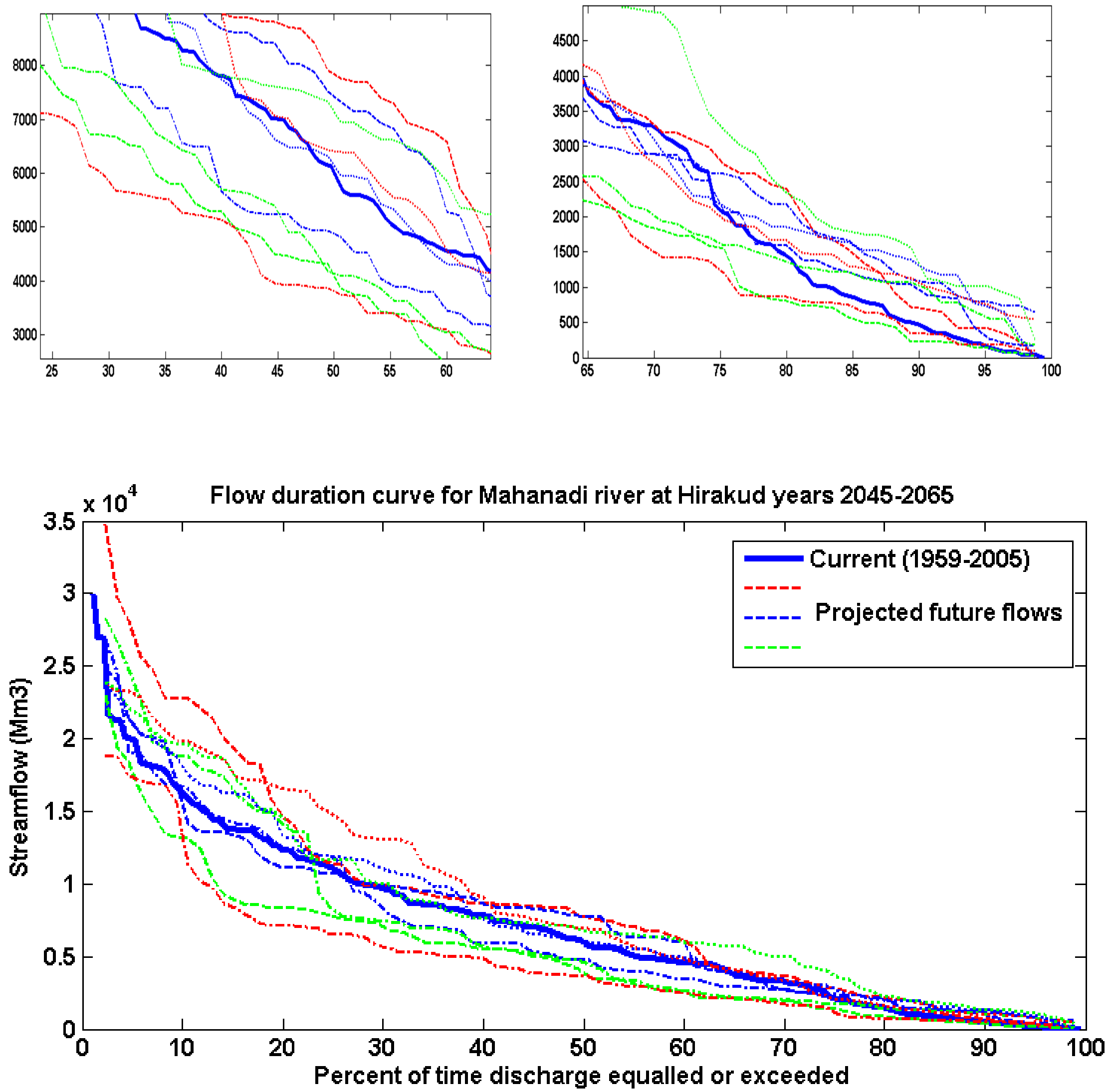


Figure 2. Flow duration curve projected under climate change scenarios for the Mahanadi river at Hirakud reservoir (Source: Raje and Mujumdar, 2010)

Figure 2 shows the flow duration curves projected for the Mahanadi River in Orissa, using several GCMs, based on scenarios provided in IPCC (2007). The flow duration curves specify the flow that may be exceeded at a given level of probability, and are used in hydrologic designs of dams, culverts, bridges, storm water drainage networks etc. The dark blue curve in Fig. 2 is the flow duration curve with the historical data. Other curves show projected flow duration curves under climate change scenarios. The mid-level flows (e.g., flows that are exceeded 40-70% of time) govern the performance of the system in terms of the water supply for irrigation and hydropower generation. With many projections indicating a likely decrease in the midlevel flows (see insets in Figure 2) it is important that the water use policies are designed to take care of the likely deficit in the coming decades. This projected decrease in streamflow is because of the likely decrease in precipitation in the region. However, as seen from Figure 2, the direction of change in the streamflow projected by different models may be different – that is, some models project an increase while others project a decrease in the streamflow. Addressing such uncertainties to provide policy makers with options of adaptive responses, is a challenging task. Raje and Mujumdar (2010) provide examples of adaptive reservoir operating policies for hydropower generation. They use the flow duration curves shown in Figure 2 and develop reservoir operating policies for the Hirakud reservoir to best maintain the reliability of hydropower generation at the current level, considering tradeoffs between hydropower, irrigation and flood control. This work is still at a research stage and needs to mature to a level where it may be transferred for actual implementation, because of the large uncertainties involved in assessment of the climate change impacts. However it is clear that the water management policies need to be adjusted to take into account the possible decreases in the inflow to the Hirakud reservoir.

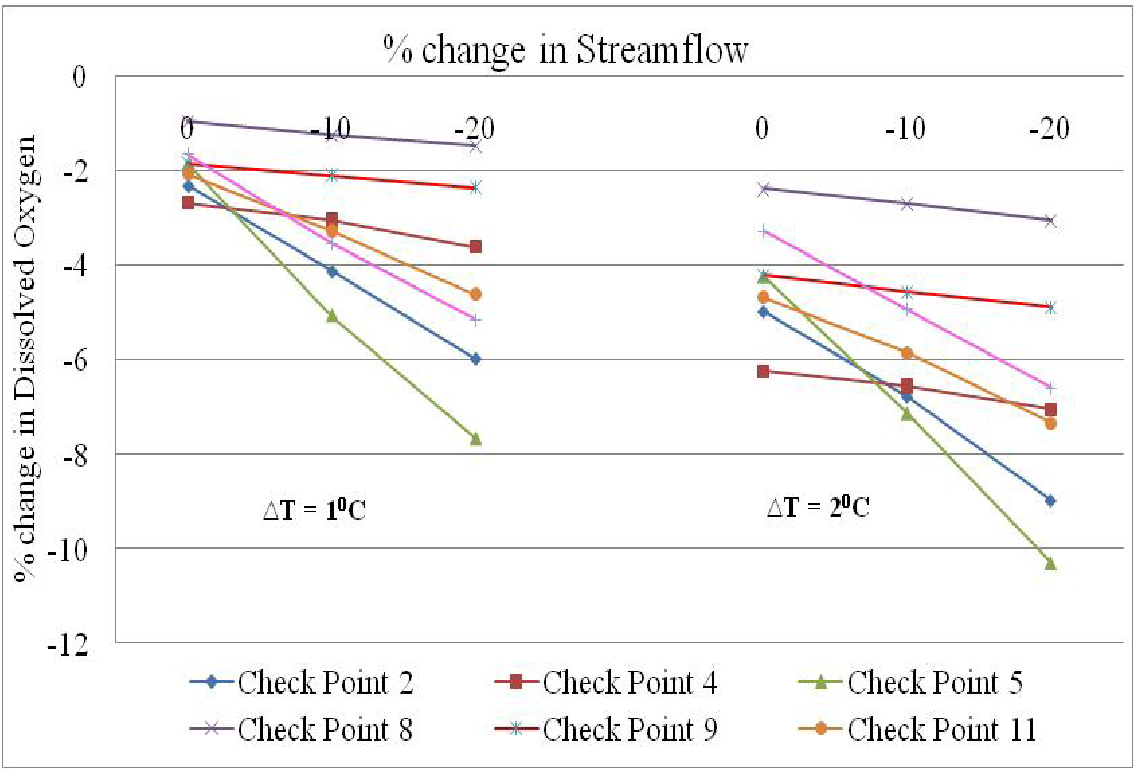


Figure 3. River water quality response to climate change (Source: Rehana and Mujumdar, 2011)

Climate Change Impacts on River Water Quality

Figure 3 shows an example of impacts of climate change on river water quality. This example is for the case study of Tunga-Bhadrariver in Karnataka, discussed by Rehana and Mujumdar (2011). Historical data analysis shows an evidence of decrease in the streamflow over the last few years in the river, along with an increase in the temperature in the region. The checkpoints referred to in the figure are locations along the stream at which the river water quality is measured/estimated. Hypothetical climate change scenarios are used to construct the graphs. The water quality (which, in this case is measured by the dissolved oxygen, DO, concentration) at a location in a stream is primarily affected by the upstream activities in terms of pollutant discharge, streamflow and air and water temperatures. The lower the streamflow, for the same levels of effluent discharges upstream of a location, the lower will be the DO level at that location, because of lower dilution effects. Similarly higher temperature, in general, implies a lower water quality in terms of the DO concentration. The hypothetical scenarios considered in the case presented in Figure 3 are combinations of (a) 1^0 and 2^0 rise in air temperature, and (b) 10% and 20% reduction in streamflows. The graphs on the left part in the figure show the response of water quality for a 1^0 rise in temperature, with points along a given line corresponding to different levels of reduction in streamflow (0%, 10% and 20%). Similarly the graphs on the right part in the figure show the response of water quality for a 2^0 rise in air temperature. A line corresponds to a particular checkpoint, as given in the legend. These results are obtained by simulating the water quality in the stream taking into account the non-point source pollution and the point sources due to industrial and municipal effluents at various locations along the stream. Details of the case study and methodology used may be found in Rehana and Mujumdar (2011). The broad level question addressed in the study is : what would be the response of river water quality if, for example, the temperature rises by 1 degree centigrade *and* the streamflow decreases by 10%, all other factors remaining the same. The results suggest that all the hypothetical climate change scenarios would cause impairment in water quality. It was found that there is a significant decrease in DO levels due to the impact of climate change on temperature and flows, even when the discharges were at safe permissible levels set by pollution control agencies (PCAs). The necessity to improve the standards of PCA and develop adaptation policies for the dischargers to account for climate change is examined through a fuzzy waste load allocation model developed earlier. Such studies are useful in revising the standards for effluent discharges in the streams. The pollution control standards may be designed to take cognizance of the extreme projected situations, or, given the uncertainties, may be designed based on the intermediate scenarios.

Impacts on Meteorological Droughts

Climate change impacts on meteorological droughts measured by the Standardized Precipitation Index (SPI) are studied by statistical downscaling and addressing uncertainties through non-parametric methods. In this approach, fuzzy clustering-based downscaling (Ghosh and Mujumdar, 2006) is used for modelling future precipitation using circulation pattern, projected with the available GCM outputs. Standardized precipitation index (SPI) developed by McKee et al. (1993) is used as a drought index which requires precipitation as an input variable. Assuming future SPI to be a random variable at every time step, methodologies based on kernel density and orthonormal systems are used to determine the nonparametric PDF of SPI. Probabilities for different categories of future drought are computed from the estimated PDF. Details of the methodology may be found in Ghosh and Mujumdar (2007). The methodology is applied to the case study of Orissa meteorological subdivision in India to analyze the severity of different degrees of drought in the future.

Fuzzy-clustering based downscaling

A statistical relationship based on fuzzy clustering and linear regression is developed between MSLP and precipitation, with reanalysis data of MSLP as predictor and observed precipitation as predictand. Gridded MSLP data used in the downscaling are obtained from the National Center for Environmental Prediction/ National Center for Atmospheric Research (NCEP/NCAR) reanalysis project (Kalnay et al., 1996). Monthly average MSLP outputs from 1948 to 2002 were obtained for a region spanning 15°–25°N in latitude and 80°–90°E in longitude that encapsulates the study region. Figure 4 shows the NCEP grid points superposed on the map of Orissa meteorological subdivision. The method involves training NCEP data of circulation pattern with observed precipitation and the use of the resulting regression relationship in modeling future precipitation from GCM projections. The training involves three steps (Ghosh and Mujumdar, 2006): PCA, fuzzy clustering, and linear regression with seasonality terms.

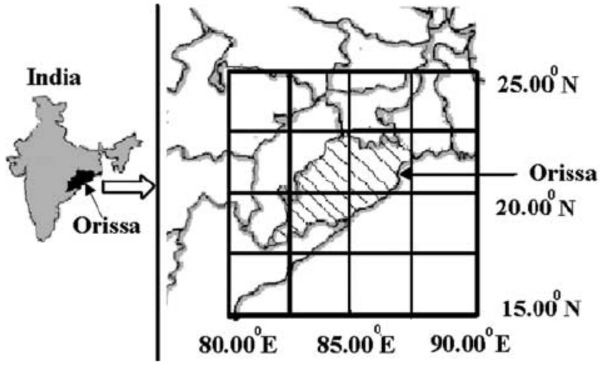


Figure 4. NCEP grids superposed on map of Orissa (Source : Ghosh and Mujumdar, 2006)

Standardization (Wilby et al., 2004) is used prior to statistical downscaling to reduce systematic biases in the mean and variances of GCM predictors relative to the observations or NCEP/NCAR data. The procedure typically involves subtraction of mean and division by standard deviation of the predictor variable for a predefined baseline period (1960-1990) for both NCEP/NCAR and GCM outputs. PCA is used to convert predictors (MSLP at 25 gridpoints) into a set of uncorrelated variables, with the first three principal components explaining 99.7% of the variability of the original data set. Fuzzy clustering is used to classify the principal components into classes or clusters. Fuzzy clustering assigns membership values of the classes to various data points. The important parameters required for the fuzzy clustering algorithm are the number of clusters (c) and the fuzzification parameter (m), which are determined from cluster validity indices like fuzziness performance index (FPI) and normalized classification entropy (NCE). Linear regression is used to model the monthly precipitation with principal components, membership values of the principal components in each of the clusters, and the cross product of membership values and principal components as regressors. An appropriate seasonality term is used to capture the seasonality. The linear regression equation is given by:

$$P_t = C + \sum_{i=1}^{I-1} \beta_i \times \mu_i + \sum_{k=1}^{K} \gamma_k \times p_k + \sum_{i=1}^{I-1}\sum_{k=1}^{K} \rho_k \times \mu_i \times p_k \qquad (1)$$

with

$$C = C^o + C^1 \times \sin(2\pi p/12) + C^2 \times \cos(2\pi p/12) \qquad (2)$$

$$\beta_i = \beta_i^o + \beta_i^1 \times \sin(2\pi p/12) + \beta_i^2 \times \cos(2\pi p/12) \qquad (3)$$

$$\gamma_k = \gamma_k^o + \gamma_k^1 \times \sin(2\pi p/12) + \gamma_k^2 \times \cos(2\pi p/12) \qquad (4)$$

$$\rho_{ik} = \rho_k^o + \rho_k^1 \times \sin(2\pi p/12) + \rho_k^2 \times \cos(2\pi p/12) \qquad (5)$$

whereP_t is the precipitation at time *t*, pc_{kt} is the k^{th} principal component of circulation pattern at time *t*, and $\mu_{it}$is the membership in cluster *i* of the principal components at time *t*. *K* and *I* are the number of principal components used and the number of clusters, respectively. β_i, γ_k, and ρ_{ik} are the coefficients of μ_{it}, pc_{kt}, and their product terms, respectively. *C* is the constant term used in the equation. The membership values μ_{it} in each cluster are assigned to the different points based on fuzzy c-means algorithm. Seasonality is incorporated by equations (2)–(5), where *p* is the serial number of the month within a year (*p* = 1, 2, .., 12). The correlation coefficient (r) between the observed and predicted precipitation is considered as the goodness of fit of the regression model. Here the r value is obtained as 0.924. The long-term mean and median of observed versus model-predicted precipitation for the wet (JJAS) and dry period shows a good match.

GCM output pre-processing

GCM grid points do not match with NCEP grid points, hence interpolation is performed with a linear inverse square procedure using spherical distances (Willmott et al., 1985) to obtain the GCM output at NCEP grid points. The eigenvectors or principal directions obtained from NCEP data are used as reference to convert the gridded standardized GCM output to the corresponding principal components.

Bias removal

The bias of annual mean of precipitation as downscaled from different standardized GCM outputs is compared to observed data for the baseline period and it is seen that even after standardization, the bias is not significantly reduced. To remove the biases, the 1961–1990 simulated mean is subtracted, and the observed baseline period mean is added, so that all the models have the same mean in the historic period, and thus the resulting uncertainty is solely due to GCM and scenario uncertainty and not due to biases present in the GCMs.
The downscaling model significantly underestimates the interannual variability most notably in the wet season. A reason for this may be the insensitivity of MSLP in correctly modelling precipitation. MSLP can partially explain historic rainfall variation, but an improvement of the model is possible if moisture content or humidity is incorporated. In the present study the analysis is only limited with MSLP because for most of the GCMs used, the outputs of moisture content or humidity are not available. The precipitation, thus computed for all the GCMs with scenarios, is converted into suitable drought indicator for examining future drought scenario.

Uncertainty modelling

The severity of future drought may be studied by estimating the evolution of the PDF of a drought indicator. The drought indicator, SPI-12 (McKee et al., 1993) values computed with downscaled precipitation from GCMs are considered as the realizations of the random variable SPI-12 in each year The PDF is estimated based on (a) assumption of normal distribution, (b) a kernel density estimation, and (c) an orthornormal series Kernel density estimation entails a weighted moving average of the empirical frequency distribution of the data. Most nonparametric density estimators can be expressed as kernel density estimators (Scott, 1992; Tarboton et al., 1998). It involves the use of kernel function (K(x)), defined by a function having the following property:

$$\int_{-\infty}^{\infty} K(x)dx = 1 \tag{6}$$

A PDF can therefore be used as a kernel function. A normal kernel (i.e., a Gaussian function with mean 0 and variance 1) is used here. A kernel density estimator ($\hat{f}(x)$) of a PDF at x is defined by:

$$\hat{f}(x) = (h\ )^{-1} \sum_{l=1}^{n} K(\ x - x_l)/h) \tag{7}$$

where$n$ is the number of observations (here number of available GCM outputs), x_l is the l^{th} observation (here SPI-12), and h is the smoothing parameter known as bandwidth, which is used for smoothening the shape of the estimated PDF.

A PDF from a small sample can be estimated using the orthonormal series method, which is essentially a series of orthonormal functions obtained from the sample. The summation of the series with coefficients results in the desired PDF. For this work, the orthonormal series as the subset of the Fourier series consisting of cosine functions is selected:

$$\phi_o(x) = 1 \text{ and } \phi_j(x) = \sqrt{2}\cos(\pi j x) \qquad j = 1,2,3... \tag{8}$$

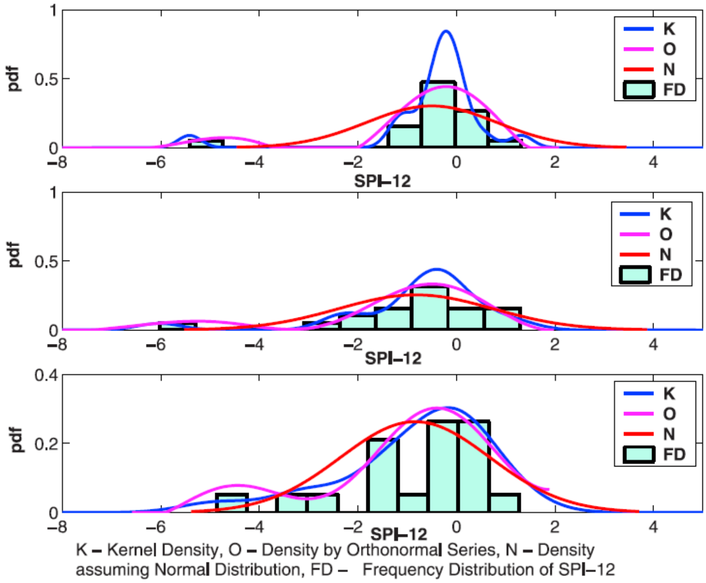


Figure 5 Estimation of PDF of SPI-12 for years 2007, 2041, and 2093 (Ghosh and Mujumdar, 2007)

The PDF of SPI-12 computed using the three methods is presented in Figure 5 along with frequency distribution of the sample for three arbitrarily chosen years 2007, 2041, and 2093 selected from the three time slices of years 2000–2010, 2040–2050, and 2090–2100. For all the cases, it is clear from the figure that a normal PDF fails to model the samples of SPI-12, especially the feature of multimodality, in all the three cases. The PDF obtained using orthogonal series closely resembles the shape generated by the frequency distribution. From the overall trend in probabilities of all categories of drought, it may be concluded that the probability of near-normal condition will decrease, and the probabilities of mild, severe, and extreme droughts will increase over time.

Impacts on Urban Floods

Urbanisation alters the hydrologic response of a catchment. Three features of the hydrograph of an urban catchment that distinguish it from the hydrograph of a non-urban catchment are : (a) the peak runoff occurs at a shorter time, (b) the magnitude of the peak discharge is higher, and (c) the total volume of runoff is larger. Time of concentration in an urban catchment is typically of the order of about an hour, and often much smaller for the sub-catchments, as against the fairly large time of concentrations of the order of about 12 hours to a few days in a river basin. These responses from an urban catchment pose a great challenge in managing urban floods. The flood-damage potential in urban areas is also high due to population and property concentration in relatively small areas. Recent catastrophic floods in Indian cities such as Mumbai, Chennai, Bangalore, Surat and Hyderabad have highlighted the importance of urban flood management in the country. Drainage systems designed to cope with extreme storm conditions are often rendered infeasible to implement because of landuse and resource constraints. Recent floods in many Indian cities have raised awareness of urban flood risk. Over the past few decades, rapid urbanization with changing land-use patterns has resulted in loss of flood-plain storage and increased runoff.

Changes in weather patterns, increasing climate variability and anticipated increases in weather extremes are expected to affect hydrologic conditions and the hydrologic responses of watersheds. The quantification of the effects of climate change is primarily based on the results of computer simulations of General Circulation Models (GCMs) for various scenarios developed based upon a number of assumptions regarding the future discharge of greenhouse gasses into the atmosphere. While GCM performance with respect to global temperature is impressive, precipitation effects are less well simulated. There are serious inconsistencies between GCMs with respect to not only the magnitude of change, but in some cases also the direction. Direct outputs of precipitation from GCMs are not generally considered reliable, and hence there has been a considerable research effort to improve the estimation of precipitation under future climate by the development of dynamical and statistical downscaling methods. In dynamical downscaling, GCMs are used to provide the boundary conditions for smaller scale regional climate models. In statistical downscaling (e.g. Wilby et al. 1998), statistical relationships are developed between the more reliable outputs of GCMs and station precipitation. Smith (1999) studied three flood prone urban catchments in south eastern Australia, to assess changes to urban flood losses for the 'most wet' and 'most dry' scenarios for the year 2070. The climate scenarios employed were from the Climate Impacts Group of CSIRO. They found that under the most wet scenario, annual average flood damage could increase within the range of 2.5 to 10 times while under the most dry scenario flood regimes would be similar to current ones. Schreider et al. (2000) modelled flood frequency and magnitude under global warming and associated rainfall intensities, and used greenhouse flood data to assess changes in the vulnerability of flood prone urban areas. They used the IHACRES rainfall-runoff model to generate future climate series of streamflow for the IPCC/CSIRO 1996 greenhouse scenarios from five different GCMs for Australia, with two approaches for generating daily climatic inputs to the model: a stochastic weather generator applied to estimate the changes in climate under double CO2 conditions, and the climate scenarios provided by CSIRO for two dates in the future: 2030 and 2070. Table 1 shows the projected changes in flood frequency corresponding to the different recurrence intervals under 2 x CO2 conditions, for two of the catchments studied. The results show that the average recurrence interval for a particular discharge is projected to decrease under the doubled CO2 conditions for all discharge values.

Table 1. Comparison of present flood frequency and that for double CO2 conditions in two Australian catchments (Source: Schreider et al., 2000)

ARI (years)	Upper Parramatta catchment		Queanbeyan catchment	
	Present discharge value (m^3/s)	ARI under 2 x CO_2 conditions for flow events of this magnitude (years)	Present discharge value (m^3/s)	ARI under 2 x CO_2 conditions for flow events of this magnitude (years)
5	86.2	2	83.4	1
10	118.2	3.3	104.8	1.8
50	252	17	158.2	5.8
100	362	44	182.2	9.4
1000	1134	400	361.4	100

ARI: Average Recurrence Interval.

Some preliminary work has been taken up at IISc Bangalore on assessing climate change impacts on urban flooding. Fig. 6 shows the historical trends in the Intensity-Duration-Frequency relationship for Bangalore city. These trends indicate that intensities for a given duration and return period are increasing. *These results are however as yet inconclusive*, *because of the rather short length of data used*. In the context of climate change, response of the short duration high intensity rainfall to large scale climatic events gains importance. Currently studies are in progress on relating the large scale climate simulations provided by GCMs with the short duration, local scale rainfall events. This task is especially challenging as a large number of local factors may govern the convective rainfall that usually causes flooding in cities like Bangalore. These issues will be discussed in the lecture.

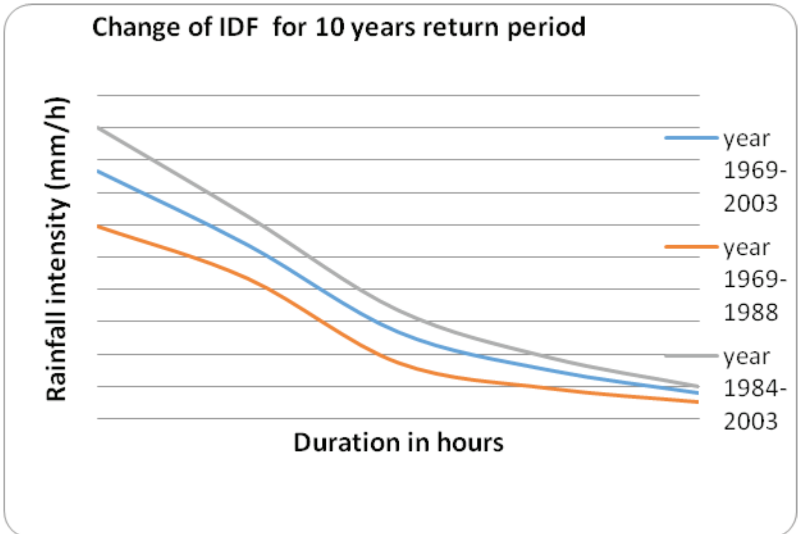


Fig. 6. Historical trends in the IDF relationships for Bangalore City

Summary

Climate change is expected to cause water stresses in several regions of the country, and is likely to exacerbate the water situation and the hydrologic extremes of floods and droughts. While the climate change projections derived from climate models are useful at large regional scales, the impacts need to be assessed at local scales. There is a considerable uncertainty associated with the exact nature of impacts on the water sector at local, river basin scales. Methodologies are available to use the projections provided by climate models in assessing local scale impacts, and quantifying uncertainties to some extent. This lecture discusses some recent studies carried out at IISc Bangalore, and brings about the concepts and issues related to climate change and variability.

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(Endnotes)

1 See symposium on ‘Automation and labor markets’, *Journal of Economic Perspectives*, Vol 29, Number 3, Summer, 2015, https://www.aeaweb.org/issues/381. The three papers in the symposium are by Autor (2015), Mokyr et al (2015), and Pratt (2015).

2 In robotics, an end effector is the device at the end of a robotic arm, which is designed to interact with the environment.

Dr. P.K Iyengar Memorial Lectures

Achieving Energy Security of India through the Advancement of Indigenous Technologies

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India's sustainable development depends on protecting the ecosystem, water resources, environment, culture, leading to clean air, drinking water, hygiene, native medicine and bio-diversity and by supporting schemes for value based education, skill development, employment, health care, housing, security, clean energy and above all higher prosperity index.

Disruptive technological innovations can only effect the most fundamental changes in the ground rules of economic competenceand environment resulting sustainable development of the society.With energy security in focus the technological advancements in solar mission, hydrogen energy, nuclear & ocean as sourceare described.

Utilisation of Thorium resource in the country& development of fusion energy to utilise the He-3 available in plenty on the moon will help energy security. In order to establish factory on the moon & process He-3, cost effective rocket system are to be developed. The use of hypersonic technology, a step higher than Bhramos supersonic missile has been addressed along with re-usability for bringing down the cost of travel to space.

Energy security will be achieved by indigenizing solar power technology with maximum efficiency using nano materials and ultimately use of solar power satellite to receive energy directly from the space, develop thorium based nuclear reactor as India has rich resource of thorium and used HE-3 from the moon as fuel for nuclear fusion power plants. Ocean provides an opportunity to generate energy utilising the thermal gradient to different depths and processing the Uranium. Advancement of science & technology with disruptive innovations will lead to energy security for the country.