CSTEP
CENTER FOR STUDY OF SCIENCE, TECHNOLOGY & POLICY

Artificial Intelligence for Climate Change Mitigation and Adaptation

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Use Cases of AI for Transport and Water Management in India

Center for Study of Science, Technology and Policy
September 2022

Designed and Edited by CSTEP

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Executive Summary

Extreme and unpredictable changes in the climate are a cause of serious concern globally. In India, the impacts of climate change are already profound. The second part of the Sixth Assessment Report (Working Group II contribution) of the Intergovernmental Panel on Climate Change (IPCC), released in early 2022, has referred to India as one of the countries to be most "economically harmed" by climate change. The situation mandates urgent nationwide measures to build climate resilience by mitigating climate-related adversities and enabling adaptation.

Among the many approaches, strategies, and technologies that are being explored to tackle the complex problem of climate change, the use of artificial intelligence (AI) is gaining prominence. In recent years, several international studies and reports have highlighted the role of AI in dealing with the perils of climate change. The use of AI-based solutions holds immense promise for advanced research, engineering, and policymaking in the climate change mitigation and adaptation domain, within different sectors such as energy, manufacturing, agriculture, forestry, and disaster management.

With the growing acknowledgement of AI's role in accelerating climate action, and some concrete efforts gaining momentum in this space in India, it is timely to examine the main aspects of AI's applicability in the area of climate action and evaluate its potential to bring about its informed and responsible deployment.

In this context, the Center for Study of Science, Technology and Policy (CSTEP) undertook a study to address some pertinent issues and questions around the applicability of AI in overcoming the challenges posed by climate change in India. The study especially investigated the potential of AI to address the climate change issues in India's transport and water sectors and enable climate action there.

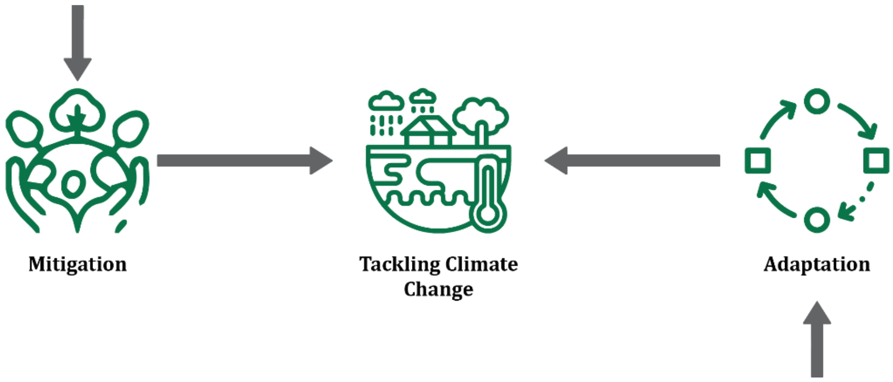
The approach and methodology followed for the study are holistic yet simple to enable a comprehensive understanding of the subject by all sections of the society. First, the use cases of AI for transport and water management (relevant to India) were identified through extensive secondary research, consultations, and case-study references. These use cases were then examined, primarily with regard to their expected outcomes, using a three-tier thematic framework developed by CSTEP. The expected outcome of a use case indicates its potential and scope to derive benefits or returns in the immediate, medium, and long term.

The study also determines the impact an AI use case can offer for tackling climate change, if leveraged as an opportunity. Depending on the kind of impact made (high or heavyweight; moderate; and uncertain), the use cases were placed under the respective impact categories. The impact and the time taken for positive returns to be visible were assessed considering parameters such as extent of usefulness in enabling climate action, progress of research and development (R&D) in the area in India, data availability and accessibility, and technology readiness.

This report, thus, features the potential use cases of AI-for-climate-action in the areas of transportation and water management, and assesses their level or category of impact, as depicted below:

Use Cases of AI for Transport Management

INTELLIGENT TRAFFIC SIGNAL SYSTEM	TRANSPORT DEMAND MANAGEMENT	SUPPLY- CHAIN OPTIMISATION	CATALYSE SHIFT TO NMT	PLAN EV CHARGING INFRASTRUCTURE	INCREASE ENERGY EFFICIENCY	INCREASE USE OF PUBLIC TRANSPORT	SHARED TRANSPORT	AUTONOMOUS VEHICLES
I: High Opportunity & Immediate E: End-User Impact	I: High Opportunity & Mid/Long-term E: Policy Enablement	I: High Opportunity & Long-term E: End-User Impact	I: High Opportunity & Short/Mid-term E: Policy Enablement	I: High Opportunity & Mid/Long-term E: Policy Enablement	I: High Opportunity & Immediate E: End-User Impact	I: High Opportunity & Long-term E: End-User Impact	I: Uncertain E: Awareness Building	I: Moderate Opportunity & Long-term E: Awareness Building



Use Cases of AI for Water Management

MONITOR GLACIAL CHANGES	FLOOD PREDICTIONS AND WARNING	RISK ASSESSMENT: FLOODS & DROUGHTS	RESERVOIR OPERATIONS OPTIMISATION	ESTIMATE GROUNDWATER RECHARGE RATE	PRECISION FARMING	URBAN FLOOD PREDICTION	OPTIMISE WATER DISTRIBUTION NETWORK	MONITOR LOSS OF WATER BODIES AND WATER QUALITY
I: High Opportunity & Mid/Long-term E: Awareness Building	I: High Opportunity & Immediate E: End-User Impact	I: High Opportunity & Mid/Long-term E: Policy Enablement	I: High Opportunity & Short/Mid-term E: Policy Enablement	I: High Opportunity & Mid/Long-term E: Policy Enablement	I: High Opportunity & Mid/Long-term E: End-User Impact	I: High Opportunity & Immediate E: End-User Impact	I: Moderate Opportunity & Long-term E: End-User Impact	I: Uncertain E: Awareness Building

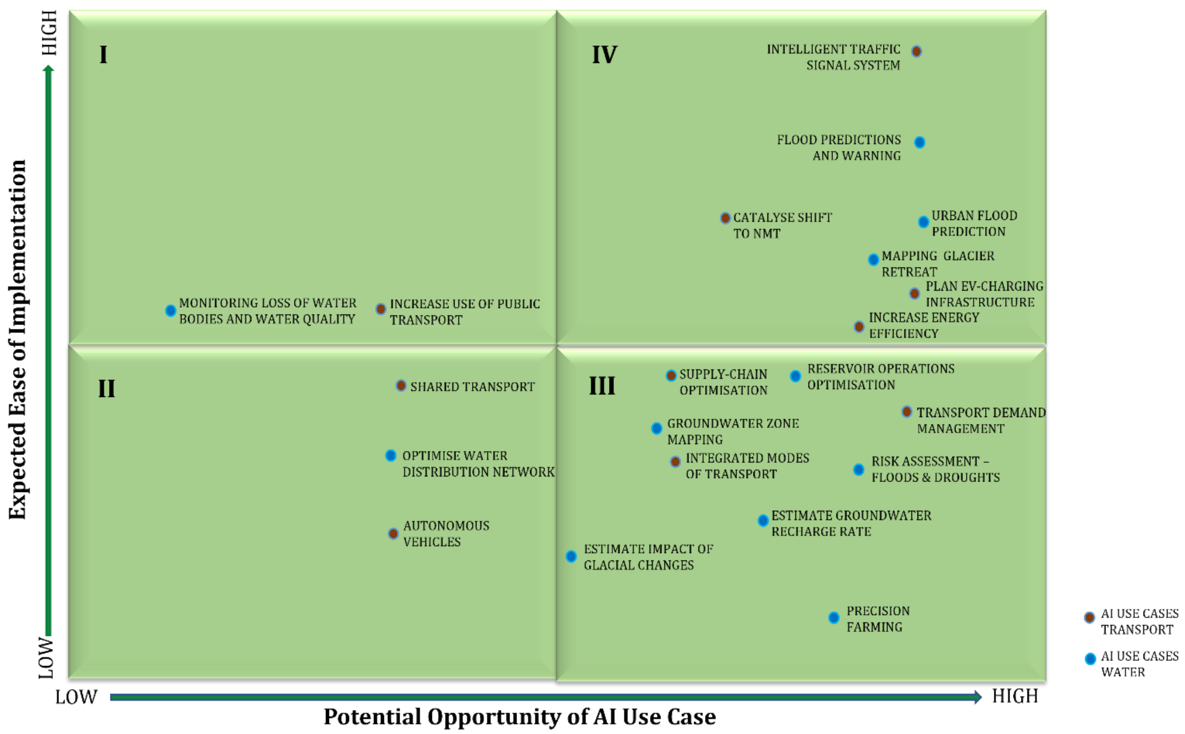
I: Impact
E: Expected outcomes (as per thematic framework)

Roadmap

Finally, the report delineates a comprehensive roadmap to guide the way forward for aligning the use of responsible AI with India's climate change mitigation and adaptation pathways in the best manner. The roadmap was designed on the basis of inputs received through critical internal reviews, consultations, and brainstorming meetings with experts.

The roadmap consists of (i) a Climate Action Matrix that can enable stakeholders to prioritise the AI use cases for implementation in India for climate action; and (ii) a set of concrete policy recommendations towards embedding AI in India's climate change mitigation and adaptation efforts at a large scale.

The Climate Action Matrix depicts each identified use case of AI in the transport and water sectors according to the potential opportunity and the expected ease of implementation in India.



Priority wise, the Matrix suggests that the use cases (or potential opportunities) of AI under quadrants IV and III could be leveraged first, as considerable work is already being undertaken in some of these areas. Moreover, their benefits are expected to outrun the costs of their implementation in the long run.

However, initiating effective large-scale action in the identified priority areas of implementation (based on the Matrix) needs the right policy push, backed by strong data infrastructure and active community participation. Therefore, this report puts together a set of actionable policy recommendations to effect AI's extensive deployment for climate change mitigation and adaptation in India.

Key Policy Recommendations

Align climate change strategies with (regulated) AI-based solutions and vice versa	• Leverage responsible AI's potential in the climate action space, and embed AI in the overall national and business strategies and vision on climate change. • Design digital innovation pathways to scale up successful pilot projects to the next level. • Include considerations of climate impact into AI regulations. • Use tools/approaches to measure and monitor AI's carbon footprint. • Explore regulatory sanctions and economic incentives to promote the use of environment-friendly AI deployment.
Develop comprehensive data infrastructure and enable data sharing	• Allow greater data democratisation and enhance access to reliable data for all relevant stakeholders and target groups. • Invite public and private sectors to host data, create data platforms, formulate data-licensing mechanisms, etc. • Establish data standards and protocols for data sharing. • Explore the formation of a nodal regulatory body or data-driven task forces in climate-critical sectors to determine national requirements and guard against unscrupulous events/incidents. • Explore international collaborations for generation of open-source climate data, technology simulations, etc.
Set up suitable physical infrastructure	• Develop the required physical infrastructure to increase the efficiency and effectiveness of AI algorithms and models addressing climate challenges. • Formulate and implement policies that promote the development of such supportive physical infrastructure.
Build capacity and promote information dissemination	• Facilitate multidisciplinary teaching and applied research in AI-for-climate-relevant fields in schools, colleges, and higher education institutions. • Invest in research and development programmes and initiatives. • Make special research grants and funding available for innovative projects. • Undertake capacity building, upskilling, and reskilling of the workforce regarding climate action through training and workshops.

	• Encourage information and data collection through crowdsourcing.
 Encourage community participation, partnerships, and collaborations	• Bridge the gap between government and research institutions, and academia and industry through multi-sectoral collaborations or consortiums to foster an AI-enabled climate action ecosystem. • Explore international collaborations to pool data, develop data-sharing standards, facilitate knowledge exchange on best practices, policy designs, technology solutions, etc. • Elicit suitable incentives and encouragement from national regulatory bodies to leverage business deals and partnerships in the AI-for-climate-action space.

This study report has undergone a systematic process of consultations and critical review from subject experts to gather their inputs, feedback, and suggestions. Thus, the report has been finalised after several revisions and iterations, incorporating learnings and information from consultative processes. A capacity-building workshop was also conducted to equip researchers with a sound knowledge of AI's practical application in the context of climate change.

We earnestly hope that this comprehensive report will prove valuable to stakeholders and audiences in the government sector, academia, research institutions and think tanks, industry, civil society, and the media.

Considering that the use of AI to tackle climate change is gathering pace, CSTEP shall continue its endeavour to push for responsible AI for climate action in India.

Contents

Figures and Tables

Abbreviations and Acronyms

AI	Artificial Intelligence
ANN	Artificial Neural Networks
AMRUT	Atal Mission for Rejuvenation and Urban Transformation
AV	Autonomous Vehicles
ARG	Automatic Rain Gauges
BEB	Battery Electric Bus
BESCOM	Bengaluru Electricity Supply Company
BOD	Biological Oxygen Demand
BMTC	Bangalore Metropolitan Transport Corporation
CAIR	Centre for Artificial Intelligence and Robotics
CAGR	Compound Annual Growth Rate
CBD	Central Business District
CSTEP	Center for Study of Science, Technology and Policy
CNG	Compressed Natural Gas
DDM	Data Driven Models
DL	Deep Learning
EV	Electric Vehicles
GDP	Gross Domestic Product
GHG	Green House Gas
HKH	Hindukush Himalayas
HDV	Heavy Duty Vehicles
ICIMOD	International Centre for Integrated Mountain Development
IMD	Indian Meteorological Department
IPCC	Intergovernmental Panel on Climate Change
INDC	India's Intended National Determined Commitments
IRBM	Integrated River Basin Management
ISRO	Indian Space Research Organisation
IWRM	Integrated Water Resources Management
LDV	Light-Duty Vehicle
ML	Machine Learning

MPOs	Metropolitan Planning Organisations
NAPCC	National Action Plan on Climate Change
NMT	Non-Motorised Mobility
NRW	Non-Revenue Water
NWP	National Water Policy
PCI	Precipitation Condition Index
PM 2.5	Particulate Matter (with a diameter of 2.5 micrometres or less)
R&D	Research and Development
RF	Random Forest
SCI	Soil Condition Index
SoC	State of Charge
SPI	Standard Precipitation Index
TCI	Temperature Condition Index
UNFCCC	UN Framework Convention On Climate Change
VCI	Vegetation Condition Index
WLS	Water-Level Sensors
WRIS	Water Resources Information System
WQI	Water Quality Index
WQC	Water Quality Classification

1. Context

1.1. Introduction

Extreme and unpredictable changes in the climate are a cause of serious concern globally today. In India, the impact of climate change is already profound. Moreover, several recent reports, such as the Sixth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC), "Climate Change 2022: Impacts, Adaptation and Vulnerability", have warned of increased risks to the lives and livelihoods of people—besides the growing threat to natural habitats—from the recurring climate variabilities. This calls for urgent nationwide measures to mitigate the adversities, as well as to enable adaptation. Among the many approaches, strategies, and technologies that are being explored to tackle the complex problem of climate change, the use of artificial intelligence (AI) is gaining prominence. It is, indeed, an appropriate time to utilise AI to predict, evaluate, and assess the risks and uncertainties associated with climate change, to strengthen climate action in India.

This report from the Center for Study of Science, Technology and Policy (CSTEP) examines the deployment of AI tools and applications for climate change mitigation and adaptation in India. Notably, it features some high-potential use cases of AI application in transport and water management. The timely report also puts forth actionable recommendations for facilitating and enabling the use of responsible AI for dealing with climate change in the country. Particularly, it delineates a comprehensive roadmap for action to enable advanced research, informed policy decisions, and mitigation strategies, and to buffer the adverse impacts of climate change in India.

1.2. Climate Change and Its Impact

With more than 80 % of its population living in districts that are highly prone to extreme hydro-met disasters (Mohanty & Wadhawan, 2021), India's vulnerability to climate change is extreme. The country's growth is intricately linked to climate risks, with a direct bearing on sustainable development and investment efforts. Besides threatening investments in infrastructure (such as housing, transport, and industries), especially along the coasts, climate risks have a disproportionate impact on vulnerable communities with low adaptive capacities, posing a critical threat to India's sustainable development (Mohanty & Wadhawan, 2021).

Like most countries, India has been struggling with intensifying climate change. This year (2022), the country went through one of the most intense heatwaves in decades. The year has already seen cyclone *Asani* claim several lives and damage thousands of acres of horticulture, paddy, and other crops across Andhra Pradesh; and extreme rainfall trigger floods and landslides in the Northeast, claiming lives and livelihoods and causing widespread destruction of crops and infrastructure. In 2020-21, Uttarakhand (situated in the northern part of India) recorded 989 incidents of forest fires damaging almost 1300 hectares of forest area due to heat waves. The state also experienced a glacier burst (also known as the *Chamoli* disaster) in early 2021 that caused flash floods and left over 200 people dead or missing, according to newspaper reports. On the other hand, the coastal regions of Odisha and West Bengal (eastern and south-eastern parts of India) were hit by a strong and damaging tropical cyclone *Yaas* in May 2021, destroying three lakh houses and dislocating 10 million people.

The second part of the Sixth Assessment Report (Working Group II contribution) of the Intergovernmental Panel on Climate Change (IPCC), released in early 2022, mentioned India as one of the countries to be most "economically harmed" by climate change.

Further, in 2021, the report "State of Climate in 2021: Extreme Events and Major Impacts" by the World Meteorological Organization (2021) pointed out that India lost almost USD 87 billion, due to natural disasters like cyclones, floods, and droughts in the year 2020, while an article published in The Lancet Planetary Health (2021) said that over seven lakh deaths in India annually (from 2000 to 2019) were linked to abnormally hot and cold temperatures.

According to the Indian Meteorological Department (2021), the average annual mean land-surface air temperature in India during 1901-2021 has shown a rising trend of 0.63 degrees Celsius, as shown in Figure 1.

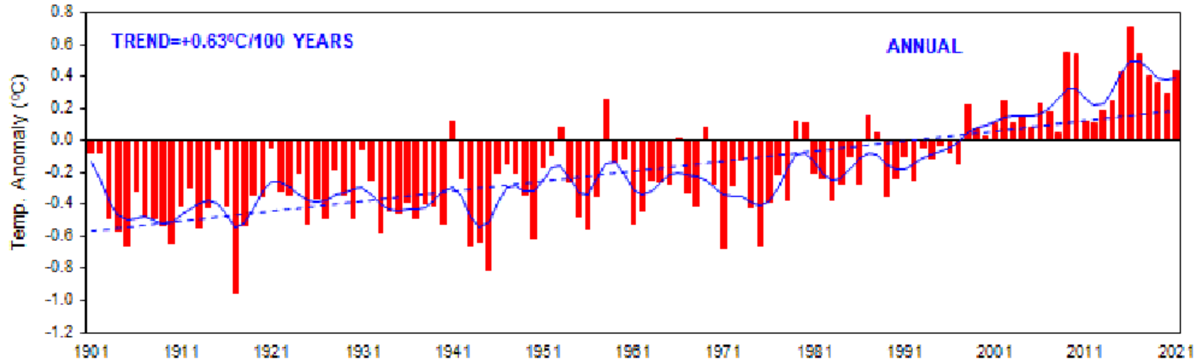


Figure 1: Annual mean land-surface air temperature anomalies (computed with 1981-2010 as base period) averaged for India (1901-2021)

***Source**: Indian Meteorological Department Press Release (2021)*

This year, India's north, west, and central regions suffered the hottest summers in 122 years, (Shukla, 2022). According to a 2020 report by the Ministry of Earth Sciences, "Assessment of Climate Change Over the Indian Region", projected that by the end of the twenty-first century, India's temperatures will rise by approximately 4.7°C to 5.5°C, and the frequencies of occurrence of warm days and warm nights will increase by 55% and 70%, respectively (Ministry of Earth Sciences, 2020).

"The average temperature in India is projected to increase by 1.1 degree Celsius – 4.1 degree Celsius by the end of the century (over the 1986 – 2005 baseline), with the rate of warming dependent on the 21st century emissions pathway"

Climate Risk Country Profile – India (World Bank Group 2021)

"Across 6 Indian port cities – Chennai, Kochi, Kolkata, Mumbai, Surat and Visakhapatnam, 28.6 million people could be exposed to coastal flooding if sea levels rise by 50 centimetres. The assets exposed to flooding will be worth US$ 4 trillion".

Climate Change 2021: The Physical Science Basis (IPCC, 2021)

Similar warnings have been sounded by various international reports on a very real possibility of India facing multiple climate-change-induced disasters over the next two decades. According to the IPCC-Sixth Assessment Report, "Climate Change 2021: The Physical Science Basis", India is expected to witness extreme weather conditions, including intense and frequent heatwaves in the coming decades. The report also says that over 40% of the Indian population will face water scarcity by the year 2050. Flooding will intensify and sea levels will rise parallelly along the coasts, making the lives and livelihoods of people located along the Indian coastline—which stretches over nine states and four union territories, covering more than 7500 kilometres—highly susceptible to climate change.

Climate change adversely impacts the public health and infrastructure of a country as well. According to the World Bank Group's 2021 report "Climate Risk Country Profile: India", heat-related illnesses, malnourishment, diarrhoea, etc. are expected to intensify due to climate change. Further, key urban infrastructure will face major challenges from temperature rises and water resource management issues. The urban and rural poor, as well as the minority groups, are likely to face higher inequality, and aggravated poverty under a climate change scenario, causing bigger damages and losses. In other words, as climate change events intensify, India is expected to witness catastrophic harm to lives, livelihoods, and habitats, all of which carry a huge economic burden.

To counter the impact of climate change, several initiatives and strategies have been undertaken by India at the national and international levels. The most significant among these are the National Action Plan on Climate Change (NAPCC) adopted in 2008 and the eight National Missions on climate change under it; India's Intended National Determined Commitments (INDC) submitted to the UN Framework Convention on Climate Change (UNFCCC) in 2015; and the Green Grids Initiative – One Sun One World One Grid (GGI-OSOWOG) launched in 2021 (The World Bank Group, 2021).

Such ambitious targets and commitments call for enforcing strict mitigation and adaptation measures nationwide and building resilience within the domestic economy and social system urgently, without compromising on the national growth and development goals. Enabling technologies like AI, when deployed responsibly, can play a crucial role here as an effective tool for upgrading and accelerating our response to climate change, and meeting our sustainable development goals.

1.3. Artificial Intelligence and Its Emergence

Prominent computer scientist and inventor John McCarthy, widely recognised as the "Father of Artificial Intelligence", described AI as the "science and engineering of making intelligent machines, especially intelligent programs". His vision and ideas changed the global dynamics in the field of technology and sparked off international debates, policy dialogue, and deliberations related to the use of technologies (AI, machine learning, computer vision, and internet of things) for data analytics, predictions, and forecasting.

In India, the growth of AI deployment can be interpreted as an S-shaped curve, manifesting a relatively slow beginning but steady gradual acceleration, owing to rising global competition and increasing awareness. AI can accelerate economic growth by enabling automation of complex real-world tasks across industries, complementing human capabilities, improving capital efficiency, and propelling innovation.

The reported statistics and data projections on AI's potential for boosting economic growth and employment generation in the country are promising. According to Accenture (2017), it is estimated that AI will add nearly US$ 957 to the Indian economy by 2035.

AI has immense potential for enhancing the growth of India's agriculture sector. AI-enabled solutions in agriculture can help farmers improve crop productivity and reduce wastage. The global market for AI in agriculture was at USD 852.2 million in 2019 and is expected to reach USD 8,379.5 million by 2030, growing at a compound annual growth rate (CAGR) of 24.8% during the forecast period (2020–2030) (Pricewaterhouse Coopers, 2022). India's national AI strategy also identifies agriculture as one of the key areas where AI can enable development and greater inclusion. In the state of Andhra Pradesh, a 30% higher-than-average yield per hectare was seen due to the deployment of an AI-powered sowing app developed by the International Crops Research Institute, (Confederation of Indian Industry, 2020). Besides agriculture, the use cases of AI in India are primarily in the fields of banking and finance, manufacturing, healthcare, public utilities and transportation, infrastructure, smart cities planning, and national defence and security (like criminal investigation, facial recognition, crowd and traffic management, digital agriculture, biometric identification, etc.).

AI is steadily becoming one of the most sought-after technology enablers in India for achieving the country's vision of becoming a USD 5 trillion global economy. Recognising the potential of AI, India has reinforced its focus on AI to enable digital transformation in the country. Various research institutes such as the Centre for Artificial Intelligence and Robotics (CAIR) are conducting research and development (R&D) on AI to gauge its application potential in different areas. Some significant milestones achieved by India in the field of AI are given in Figure 2.

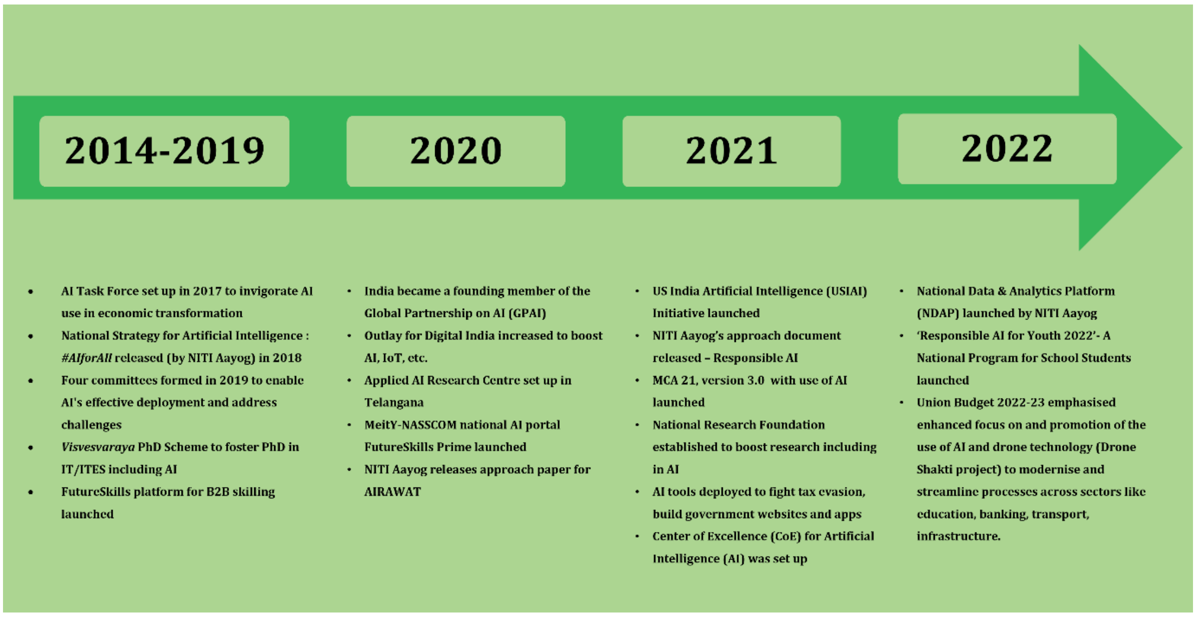


Figure 2: Milestones achieved by India in the field of AI

Union Budget 2022-23 described AI as the "sunrise technology that would assist sustainable development at scale and modernise the country". In keeping with this vision, India has, in recent years, put forth considerable budget outlays for R&D and deployment of AI across different sectors. Also, the NITI Aayog released a discussion paper "National Strategy for Artificial Intelligence #AIFORALL" in 2018, which discusses strategies on using AI for climate action. Thus, the conditions are favourable for leveraging the potential of AI to help tackle one of the most pressing problems of our times—climate change.

1.4. Intersection of AI and Climate Change

AI is a powerful tool that can be applied to address the many challenges posed by climate change. It can provide solutions that are useful for advanced research, engineering, and policymaking for climate change mitigation and adaptation. There are a considerable number of opportunities for applying AI and machine learning (ML) for climate action. Some of the key roles that AI can play in aiding climate change adaptation and mitigation efforts are described in Figure 3.

Figure 3: Key roles of AI in the climate action space

There are several sectors where AI can facilitate climate action. These are described in Figure 4.

Figure 4: Sectors where AI can facilitate climate action

Over the years, several international studies and reports have highlighted the role of AI in dealing with the perils of climate change. For example, Rolnick et al. (2019) in their published research, described how machine learning can be a powerful tool in reducing greenhouse gas (GHG) emissions and helping society adapt to a changing climate. Similarly, a report by Kaack et al. (2020) says that AI can facilitate climate change mitigation and adaptation strategies within different sectors such as energy, manufacturing, agriculture, forestry and disaster management. The report also warns of AI's detrimental outcomes (for instance AI can lead to increasing consumer demand for high-carbon alternatives like shared transport, resulting in increased GHG emissions). It is, thus, imperative that the use of AI for climate action aims at the overall well-being of the society. A report by the Global Partnership on Artificial Intelligence, Climate Change AI, and Centre for AI & Climate (2021) emphasised that governments across the world must devote resources to promote responsible adoption of AI for climate solutions. Responsible and efficient deployment of AI for tackling climate change can be a potential game-changer for India.

2. Objectives and Relevance of the Study

Given the climate crisis the world is in now, and the acknowledgement of AI's role in accelerating climate action, it is apt to study the main aspects of AI's applicability in this area and evaluate its potential to effect its informed and responsible deployment.

This study addresses some pertinent issues and questions related to the applicability of AI in overcoming the challenges posed by climate change in India. The approach and methodology followed for the study are holistic yet simple to enable a comprehensive understanding of the subject by all sections of the society. Therefore, we believe that this report will prove valuable to stakeholders and audiences in the government sector, academia, research institutions and think tanks, industry, civil society, and media.

The following are the expected outcomes of this study:

1. *Enablement of AI deployment for climate change mitigation and adaptation in India's mainstream national agenda and strategy.* Guided and informed policy decisions on national and state strategies governing the subject.
2. *Identified opportunities for climate change mitigation in transport management and adaptation in water management.* On the basis of the impact assessment of each of the opportunities presented, government bodies, research groups, academics, public and private sectors, and civil society organisations can prioritise the ones they want to invest in to assess, analyse, and achieve the desired outcomes.
3. *Improved outreach, literacy, and awareness of AI in general, and of AI for climate change in particular, including the opportunities and risks associated with AI deployment in this area, the nature of tools, standards, and best practices, etc.* The insights provided in this report are expected to improve knowledge on the subject globally, and especially in India, for all relevant stakeholders (government bodies, research groups, academics, public and private sectors, and civil society organisations working in climate-relevant fields).
4. *Enhanced capacities and skills of relevant researchers and institutions towards developing AI-related technical expertise to deploy AI-for-climate solutions.*
5. *Improved and accelerated R&D and advanced studies on AI and AI for climate in and for India to balance out the international narratives on the subject.* At present, the global initiatives in this field are largely driven by the developed countries. This needs to change to factor in the emerging countries' efforts. This report will enable advanced research and innovation from this standpoint as well, and serve as a ready reckoner for researchers and engineers working in this area.
6. *Greater applicability of disruptive technologies such as AI in the context of India's specific needs, policies, data, and technology maturity vis-à-vis the desired impacts and benefits.* This, in turn, would facilitate exploration of possible solutions not just from the viewpoint of technological advancement and feasibility, but also in terms of potential impact and adoption.
7. *Enhanced and wider scope for partnerships, collaborations, and investments, and reinvigorated start-up culture in the field of disruptive technologies to tackle climate change impacts.*

3. Approach and Methodology

Before initiating this study, we undertook a background study to arrive at the area most suitable for examining the use cases of AI and assessing their impacts. This entailed developing a holistic understanding of the different ways in which AI can enable a positive impact in the climate change mitigation and adaptation space. We especially investigated the potential of AI to address the climate change issues in India's transport and water sectors and enable climate action there.

This study was undertaken with the overarching objective of arriving at the use cases of AI in the transport and water sectors, which would help in addressing the challenges posed by climate change in these sectors in India. It also aims to guide future research and development by providing a prioritising matrix to indicate the extent of impact the use cases can create in the climate change mitigation and adaptation space, and putting forth a set of concrete policy recommendations and actionable suggestions for climate action.

Further, considering the lack of awareness on the subject in India, a capacity-building workshop was organised for the researchers, academicians, and practitioners at CSTEP to enhance their knowledge and understanding of this field.

The process and methodology adopted for the study is summarised in Figure 5.

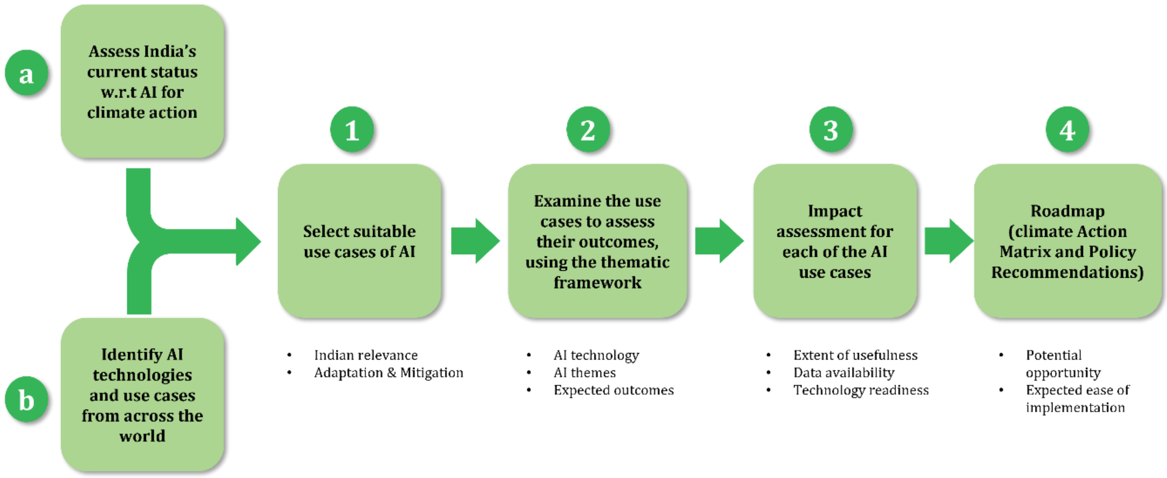


Figure 5: Summary of steps followed in the study (methodology adopted)

These steps, along with the methodology, are detailed in this section.

Preliminary research and assessment largely involved taking stock of the existing climate change situation in India, and examining the interlinkages or intersections of AI and climate change. Next, the use cases of AI for transport and water management (relevant to India) were identified through extensive secondary research, consultations with the relevant experts, and references on cases-studies in this field from several countries. Each of the AI use cases was then examined using a thematic framework developed by CSTEP for the study.

Thematic Framework: As shown in Figure 6, the thematic framework consists of three levels. Level I includes the fundamental AI-technology solutions—which forms the basis of the use cases. Each of the use cases is examined in the context of the solution (core AI technology, reusable AI platforms, and base climate data) they offer. Level II of the framework assesses the use cases through an AI-themed lens. The themes of Level II are manifested in the technology solutions offered by the use cases in Level I. For instance, data enrichment and augmentation can be achieved by those use cases where AI enables base climate data collection. Level III contains the expected outcomes of the use cases—the most important part of the framework.

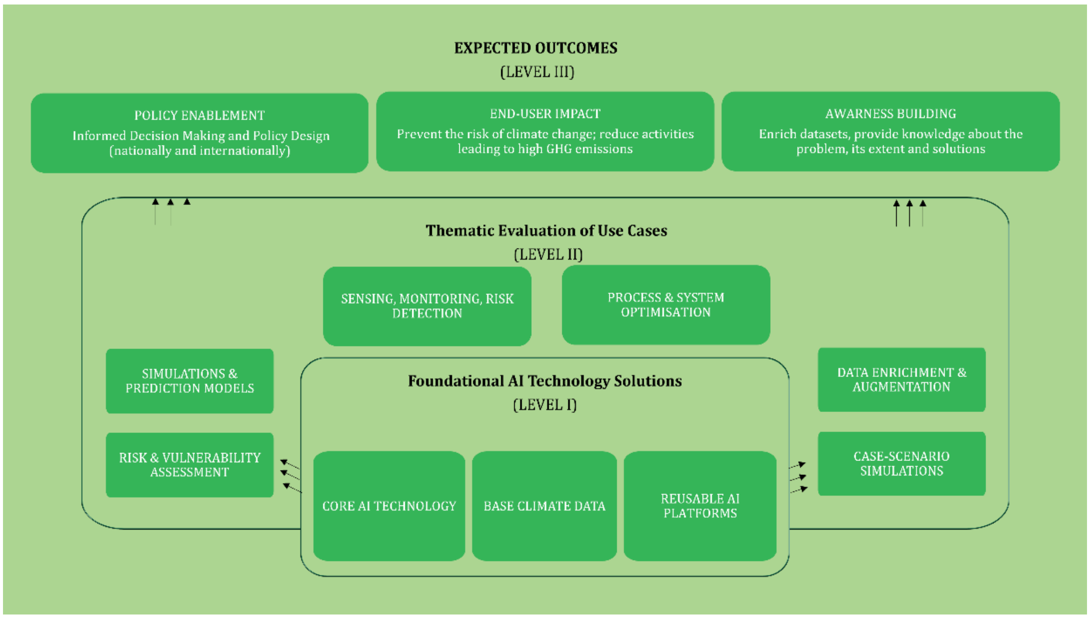


Figure 6: Thematic framework

Based on the Level II theme under which the use case falls, its expected outcome in Level III is assessed. For example, use cases that fall under the theme of “simulation and prediction models” or “risk and vulnerability assessment” are expected to be useful in policy design or policy enablement. Similarly, use cases falling in the category of “sensing, monitoring, and risk detection” and “process or system optimisation” are expected to achieve end-user impacts, such as disaster prevention. Each use case of AI was examined through this framework to determine the expected outcome it would attain. The expected outcomes of the use cases can be measured in terms of the end-user impact (e.g. process optimisation, policy enablement), and also in terms of the type of knowledge generated (e.g. opportunities for advanced research or development of dashboards, observatories for assessing climate change). Thus, the thematic framework offers a direction for research, capacity building, policymaking, and institutional actions, with the aim to better align AI with climate change strategies.

Impact Assessment and Categorisation: The study also determines the impact a use case of AI can offer for tackling climate change, if leveraged as an opportunity. Depending on the kind of impact made, three impact categories have been created; (a) high or heavyweight; (b) moderate; and (c) uncertain, as explained in Table 1 below. The impact and the time taken for positive returns to be visible was assessed on the basis of parameters like extent of usefulness in enabling climate action, progress of R&D in the area in India, data availability and accessibility, and technology readiness.

Table 1: Impact Categorisation

HIGH or HEAVYWEIGHT OPPORTUNITY	This implies that the specific AI use case/AI application presents the opportunity or potential to have a significant impact on climate change mitigation or/and adaptation efforts, and must be pursued. The opportunity (AI use case), if pursued or invested in, can realise guaranteed benefits/returns over the mid to long term (and immediate in some cases).
MODERATE OPPORTUNITY	This implies that the specific AI-driven use case/AI application presents the opportunity or potential to have a not-very-significant impact on climate change mitigation or/and adaptation strategies, and could be pursued as an alternative option or in conjunction with other options, but not as the primary one. The impact can be observed over the mid to long term.
UNCERTAIN IMPACT	This implies that the impact of the specific AI-driven use case/AI application is uncertain on climate change mitigation and adaptation efforts. More research is needed to assess the likely impact.

Roadmap (Climate Action Matrix +Policy Recommendations): As the final part of the study, a roadmap providing the way forward for aligning the use of AI with India's climate change mitigation and adaptation pathways in the best manner has been developed. The roadmap consists of (i) a Climate Action Matrix that identifies the potential use cases of AI that can be taken up in India to effectively tackle climate, and also prioritises them for implementation (figure given under the "Roadmap" section); and (ii) policy recommendations towards embedding AI in India's climate change mitigation and adaptation efforts at a large scale.

It is pertinent to note that during the selection of use cases, we have been liberal in judging the applicability of AI to address the issues at hand. We are also cognisant of the fact that not all use cases have a proven antecedent or solution yet. However, we believe that our responsibility is to first present the nature and set of possibilities that could potentially benefit climate action. Technology solutions can mature, and newer or innovative ways to leverage technology can be found out, if policymakers, stakeholders, and the relevant organisations are first made aware of the range of possibilities.

At the same time, it needs to be noted that the evaluation criteria presented in this report are based on the current understanding and maturity of the technology available for use. Research in this area is evolving and expanding at a rapid pace, with newer technological development and richer data sets coming in almost every day. Thus, some of the use cases that are judged infeasible today can become feasible in the future with the right choice of technology deployment and policy interventions.

4. AI for Transport

The transport sector is essential for the economic growth of any nation. However, it is also a major GHG emitter. The Indian transport sector is under acute stress due to poor infrastructure, growing population, urbanisation, increased vehicular traffic, and cargo volumes. These challenges directly or indirectly lead to increased emissions. Indian's transport sector is responsible for 13.5% of the country's energy-related CO2 emissions, and is the third highest contributor to India's total GHG emissions (Climate Analytics & NewClimate Institute, 2020). Without sustained mitigation policies, emissions from the sector can double by 2050 (United Nations Environment Programme, 2020).

In India, the transport sector contributes around 6.4% share of India's Gross Domestic Product (GDP). Within the sector, road transport is the most dominant, carrying 90% of passenger and 65% of freight traffic, and making a GDP contribution of 5.4%. Road transport forms approximately 90% of the total CO_2 emissions (mainly by way of fuel burning by vehicles), followed by civil aviation (6%), railways (3%), and domestic water transport (1%) (MoEFCC, 2021).

Road transport in India has witnessed remarkable growth and is expected to continue to grow at a significant rate in the coming years. The current projections indicate that road traffic will grow by more than 5 times from 2012 to 2031-32, with freight traffic reaching 6559 billion tonne-km (one tonne over a distance of one kilometre), and passenger traffic reaching 163,109 billion passenger-km (conveyance of one passenger by a defined mode of transport over one kilometre). It is estimated that energy consumption by passenger vehicles will increase by 3.7% to 5.5% annually, and that by freight transport will increase by 4.6% to 7.2% annually. Further, emissions from cars—which form a major share of transport-related PM2.5 emissions—are expected to grow by 2.6 times by 2050. This would exacerbate air quality problems and create hurdles in meeting the long-term climate mitigation goals (Paladugula et al., 2018).

The management of road transport is, thus, essential for effective execution of emission-reduction strategies. Interventions are primarily required in the areas of planning, maintenance, and operations of transportation systems to reduce GHG emissions. Machine learning can help in prompt implementation of such interventions, for example, by providing better demand forecasts.

The application of AI in the transport sector carries great potential. The market size of AI in transport is expected to grow from USD 18,520.0 million in 2020 to USD 44,885.8 million by 2026, registering a CAGR of 17.5%. The rapid growth of this market is driven by the many benefits AI can deliver in terms of increased transport efficiency, pedestrian and driver safety, lower costs, traffic pattern scanning, and route optimisation to minimise CO2 emissions.

4.1. Transport Management: Use Cases of AI

Besides a poor infrastructure, India's transport sector is stressed due to increase in vehicle traffic, cargo volumes, and use of fossil fuels caused by the growing population and urbanisation. Since these factors are interconnected, an intervention that is targeted towards overcoming a particular challenge is likely to have an impact on others as well.

The use cases of AI in the transport sector have the potential to significantly limit GHG emissions, and can, therefore, can be instrumental in mitigating climate change impacts. According to the findings of the survey "Climate AI: How artificial intelligence can power your climate action strategy" conducted by Capgemini Research Institute (2021), the use cases of AI in the automotive sector led to an average reduction of over 12% in global GHG emissions during the years 2018 and 2019. Further, the survey reports that the emission reduction on an average over the next 2-3 years is expected to be over 15% (if AI use cases are deployed in the automotive sector).

Depending on the kind of mitigation impact they have, the AI use cases in the transport sector identified under this study have been clubbed under the following categories: (i) reduction in traffic activity; (ii) transition to clean transport; and (iii) modal shift. Their expected outcomes were assessed using the thematic framework. Further, an impact assessment exercise was also carried out to provide a comprehensive understanding of each of the use case of AI in terms of its overall impact on climate change mitigation. A Climate Action Matrix which prioritised the use cases depending on the potential opportunity and ease of implementation was developed.

A summary of all the use cases of AI in the transport sector—along with their thematic framework evaluation, the necessary datasets required for their measurement, and their expected outcomes—is given in *Appendix I*.

Here we describe each one of them in detail, along with their potential impact.

4.1.1. Reduction in traffic activity

Indian cities have one of the worst traffic conditions worldwide. According to the TomTom Traffic Index (2021), the city of Mumbai ranks fifth globally, with a congestion level of 53%; this implies that travelling within Mumbai city takes about 53% more time than usual. Further, the report indicates that an average Mumbai resident wastes approximately 121 hours a year stuck in traffic jams. The city of Bengaluru is at the tenth position with a 48% congestion rate, and the union territory of New Delhi (also with 48% congestion) is ranked eleventh. Apart from these, the city of Pune features in the index at the twenty-first position, with a congestion rate of 42%.

An increase in the severity and duration of traffic congestion increases GHG emissions. As time vehicles spend more time on the road during congestion idling or crawling, they undergo numerous acceleration and deceleration events, leading to higher GHG emissions. A study by Goel et al. (2016) have indicated that an increase of about 51% in travel time (under congested conditions) can lead to 53% more CO_2 emissions.

An increase in traffic and congestion often leads to the expansion and development of road infrastructure—seen as a solution to this problem. India's road networks have grown by about 30% over the past decade. At the same time, vehicle registrations have risen by almost three times, adding to the congestion. Therefore, creating more road space alone cannot be a solution. Simultaneous policy interventions targeted at reducing traffic activities are needed, which AI can help with.

AI deployment for reduced vehicular activity

Strategies that can be adopted to reduce the overall vehicular activity on roads include reduction of idling time by better management of traffic, use of energy-efficient routes, demand management, and process optimisation. AI can play a significant role in achieving this, thus helping solve various associated issues like transport-related safety, unreliability and unpredictability of public transport, poor energy efficiency etc.

In the following section, we examine how AI can be deployed to reduce traffic and ease traffic congestion through intelligent traffic signal systems, demand management, and process optimisation.

4.1.1.1. Intelligent traffic signal system

High opportunity | Immediate

An intelligent traffic signal system uses vehicle location and movement information from registered vehicles, as well as the necessary modifications required in non-motorised vehicles plying on roads. The application is an overarching system of optimisation, accommodating other mobile applications such as transit signal priority, freight signal priority, emergency vehicle pre-emption, and pedestrian mobility to maximise overall arterial network performance. In addition, the application may consider additional inputs such as the weather conditions or the interfaces (i.e. traffic flow) between arterial signals and ramp meters.

A study by Navarro-Espinoza et al. (2022) proposed the use of ML and deep learning (DL) algorithms to predict traffic flow at intersections. This lays the groundwork for adaptive traffic control, which can be done either by remote-controlling traffic lights or by applying an algorithm that adjusts the timing according to the predicted flow. The number of vehicles sampled every 5 minutes at six different intersections over a period of 56 days (using different sensors) were used as the dataset in their study. They found that Multilayer Perceptron Neural Network (MLP-NN) produced better results and took less training time, followed closely by Gradient Boosting, Recurrent Neural Networks (RNNs), and finally Random Forest, Linear Regression, and Stochastic Gradient. All ML and DL algorithms scored well on performance metrics, indicating that they are feasible for deployment in smart traffic light controllers.

There is evidence to show that intelligent traffic control systems are quite effective in conservation of energy and the environment. A 2002 study by the Organisation for Economic Cooperation and Development (OECD) revealed that intelligent traffic control signals at 3172 locations in California reduced fuel consumption by almost 9%. A real-time adaptive traffic control system called Scalable Urban Traffic Control (Surtrac) has been developed as a research project at Carnegie Mellon University and was rolled out around Pittsburgh by Rapid Flow Tech Company. The system uses video feeds to automatically detect the number of road users, including pedestrians, and types of vehicles that are at an intersection. The AI software then processes this data second-by-second to arrive at the best way to move traffic through the intersection, changing traffic lights accordingly. It was used at 50 intersections in Pittsburgh and reduced wait times at intersections by up to 40%, according to the company. It is also reported that *Surtrac* has caused a 25% reduction in the travelling time in Pittsburgh city and a drop of up to 20% in vehicular emissions (Rapid Flow Technologies, 2021).

Similarly, AI and ML are also being used to check traffic violations at zebra crossings and for lane detections. According to Lozano Domínguez et al. (2020), ML techniques could be applied to sensory detection of vehicles in crosswalks. Further, DL solutions can be used for lane detections (Virgo, 2017). Intelligent transport systems driven by AI-based solutions reduce traffic congestion, ensure compliance to traffic rules, and are slowly turning smart cities into a reality.

Therefore, this use case of AI has the potential to have a high positive impact in the area of climate action.

Impact Assessment for India

In India, traffic data (such as the number of road users and pedestrians, traffic density), and information on intersections and types of vehicles at an intersection is not readily available. AI can be deployed to gather these big and raw datasets from traffic video feeds which are accessible. In Bengaluru (India), where traffic jams are common, Siemens Mobility built a prototype monitoring system that uses AI through traffic cameras to detect vehicles and calculate the density of traffic on the road, and alters traffic lights based on real-time road congestion (Lopez Conde & Twinn, 2019). The use case will result in high positive returns in terms of reducing the overall traffic activity, and hence traffic congestion on roads. Moreover, it would certainly lead to efficient fuel consumption by vehicles and reduction in overall emissions. With the availability of datasets, intelligent traffic signal systems can prove to be a solution to traffic congestions in the short term, with immediate and direct impact on the end users.

Evaluation as per the framework: This use case of AI has the potential to derive end-user impact through processes and systems optimisation through real-time capturing of traffic information and analysis.

4.1.1.2. Demand management

High opportunity | Mid to long term

Demand management uses information and technology to dynamically manage demand, including redistribution of travel to lower congestion periods of day or routes or reducing overall vehicle trips by influencing a mode choice. Modelling demand and planning infrastructure will provide new transport routes to people, significantly shaping their decisions regarding the number of long trips and the transport modes chosen.

In this case, ML can provide information about mobility patterns and demand, which is necessary for agent-based travel demand models—one of the main transport planning tools. It can also deduce information from novel data, such as smart card data, mobile phone sensors, etc., to learn about the behaviour of public transit users, personal travel demand, and the urban topology. This makes it possible to estimate origin-destination demand and road traffic forecasting.

On the basis of the demand predicted and the travel patterns learned, new public transportation links (especially for daily long trips) can be created to provide more comfortable transport to passengers. This will encourage passengers to commute by public transport rather than private modes, leading to reduced traffic activity, and hence reduced GHG emissions.

Wipro—an IT business company in Bengaluru—worked with the Bangalore Metropolitan Transport Corporation (BMTC) to manage its employees' travel demand by designing specific routes for workers to travel efficiently. This collaboration improved employees' user experience, reduced costs, and shifted commuters to buses rather than private vehicles, reducing employee GHG footprint by almost 16% in the first year of implementation. According to Kodransky (2009), demand management of transport will be very effective in developing countries, as a fairly large population is dependent on transportation modes other than private vehicles, and improvements to these modes will provide large benefits to users and the society in general.

Impact Assessment for India

Managing and modelling demand (using ML) can play a major role in reducing the overall traffic activity. It can help in discouraging traffic sprawl by creating new transportation links on the basis of predictions and travel pattern analyses.

ML-based modelling of demand can help mitigate climate change by improving the operational efficiency of modes that emit significantly less CO_2. The most important datasets needed for this are the travel patterns and behaviour of passengers, the collection of which requires passenger participation.

Once datasets are available, prediction and modelling of demand can help in better traffic management, resulting in reduction of GHG footprints. Prediction and modelling of demand gives ample opportunities and information to policymakers for devising strategies and policies to reduce travel demand, or to redistribute demand in space and/or in time, thus impacting the travel behaviour of passengers. The impact of this use case can be witnessed over the mid to the long term, since it involves substantial information gathering on travel patterns and behaviour of passengers, which are quite uncertain and erratic usually. Also, as that predictions and modelling exercises are not 100% accurate, some uncertainty will always remain. In other words, this use case cannot be considered independently, and must be used in addition to or be accompanied by other use cases of AI.

Evaluation as per the framework: This specific use case of AI is expected to ensure effective policy enablement through data enrichment and augmentation and simulations and prediction models.

4.1.1.3. Process optimisation

High opportunity | Long term

Process optimisation (e.g. supply chain optimisation) can be crucial and highly beneficial in reducing GHG emissions. With rising income levels, higher exports, a rapidly growing e-commerce sector, and a growing retail sales market, the demand for goods movement is expected to increase at a 7% CAGR, leading to increase in the supply chain requirements (NITI Aayog et al., 2021).

A smarter supply chain management that uses AI, can help in process optimisation, in turn, leading to a reduction in traffic activities. Supply chain optimisation is a series of decisions that impact upstream and downstream processes. Data-driven approaches leveraging AI can enable organisations to take these decisions effectively. ML offers opportunities to optimise complex interaction of shipment sizes, modes, origin-destination pairs, and service requirements through mixed-integer linear programming. Freight consolidation (which refers to bundling shipments together) drastically reduces the number of trips taken (and therefore the GHG emissions). AI-based inventory management that uses an automated and continuous learning approach will make it highly accurate and resilient against uncertainties in demand and supply. AI can also be used for last-mile delivery optimisation to help decrease cost, increase service levels, maximise resource utilisation, and reduce carbon emissions.

ML can also assist in improving vehicle efficiency. Trucks, which are high GHG emitters, can particularly be cost-competitive, trying to benefit from overloading, which often decreases efficiency. ML and image recognition can help detect overloading of trucks, which can be a useful piece of information for public institutions that enforce overloading laws and regulations.

India's logistics sector comprises over 10,000 types of products and has a market size of INR 11 lakh crore. It is expected to grow into a market of INR 15 lakh crore by 2022 (NITI Aayog et al., 2021). Around 71% of India's freight is transported by road and truck productivity here is lower than the global standards. For example, trucks in India travel about 300 km per day, as compared to the global average of 500 to 800 km per day. Also, their empty running rates are as high as 40% (28-43%) (NITI Aayog et al., 2021), which implies more driving to move the same amount of goods, leading to high costs and a higher rate of emissions. Therefore, effective use of AI- or ML-driven supply chain optimisation would enable clustering suppliers by their geographical location and common shipping destinations, thereby increasing the efficiency of the resources, and managing demand and supply, as well as warehouse logistics properly.

Impact Assessment for India

With almost 75% of the freight market run by small owner-operators (who own up to five trucks), the logistics market is highly fragmented in India. Big fleet operators that own over 20 trucks) make up only 10% of the market. India's warehousing sector is also highly fragmented, with unorganised market players owning 90% of the market, and most warehouses being small and localised.

In such a scenario, it could be difficult for small players to use AI to optimise driving patterns, since they lack the expertise required to operate, and have comparatively lower abilities to invest, and access digital tools and software. Therefore, penetration of AI-enabled solutions could take a while in the logistics sector of India. The acceptance and use of AI-driven solutions among the smaller market players especially, can take off only gradually, once they are aware about the benefits and have the necessary skill-sets, wherewithal, and capacities.

According to NITI Aayog's 2021 report "Fast Tracking Freight in India", optimising truck use can reduce annual CO_2 emissions by 185 million tonnes by 2050. While it is a potential high opportunity use case, the overall impact of process optimisation in India cannot be properly assessed unless there are adequate policy measures to reduce fragmentation of the logistics industry, and to undertake capacity building, and awareness campaigns on AI-enabled solutions for the small firms and market players in this sector. Therefore, the impact could be visible over the long run after necessary policy measures and capacity building exercises have been undertaken.

Evaluation as per the framework: This specific use case of AI has the potential to derive end-user impact through processes and systems optimisation.

4.1.2. Transition to clean transport

In India, which has the third-largest road network in the world, the total number of vehicles in the fiscal year 2019 stood at 295.8 million. Most of the vehicles' fuel type is either petrol or diesel. The estimated fuel consumption by road transportation in 2020 was 92 (87–95) megatonne (Mt), where 61% (55.67 Mt) comes from diesel, 36% (32.87 Mt) from petrol, and 4% (3.23 Mt) from CNG. There has been a 9% increase (from 51 Mt to 56 Mt) in diesel consumption, and a two-times increase in petrol consumption (from 15.7 Mt to 32.87 Mt) in a decade (2010 to 2020) in the road transport sector (Singh, Mishra et al., 2021). The increase in consumption of petrol between the years 2010 to 2020 was due to an increase in private modes of transport (primarily two-wheelers and petrol-fuelled cars), while diesel consumption increased mainly due to an increase in freight transport.

The total CO_2 emission for 2020 was estimated to be 274 (265–292) teragram (Tg), with diesel-fuelled vehicles making a significant contribution of 61%, followed by petrol vehicles (37%) and CNG vehicles (2 %). Freight vehicles (HDV and LDV) fuelled by diesel contributed 38% (104 Tg) and private transport vehicles contributed 36% (97.5 Tg) (Singh, Mishra et al., 2021).

AI's deployment to catalyse clean transport transition

Dependency on fossil fuels (which cause GHG emissions) is one of the major causes of climate change. As such, it is essential to shift to clean transportation to prevent further increases in emissions. While transitioning to clean transport is dependent on various factors such as cost, maintenance, policies, user's will, etc., technology can act as a catalyst to accelerate the shift. Clean transport transition mainly involves a shift to either electric vehicles (EVs) or to non-motorised transport (NMT).

4.1.2.1. Shift to NMT

High opportunity | Short to mid term

One way to catalyse the use of NMTs for last-mile connectivity is to provide suitable and reliable infrastructure for enhancing usability. According to Advani and Tiwari (2006), 24% of the Delhi metro trips are dependent on rickshaws as feeder modes. An increase in the share of travellers using NMT for last-mile connectivity will, therefore, reduce traffic and GHG emissions. The infrastructure available for cyclist and pedestrians is limited. By crowdsourcing satellite imagery, the existing NMT infrastructure at major transport hubs can be assessed and gaps can be identified. AI-driven prioritisation of infrastructural needs can be done on the basis of demand and awareness.

Bike sharing and electric scooter services can also be sustainable alternatives for urban mobility. They do not require ownership and integrate well with public transportation. A recent study by the Center for Study of Science, Technology and Policy (2022) found that if the average share of NMT and public transport in Indian cities increases by 20%, GHG emissions from urban passenger transport can reduce by 10%. ML studies help to understand how the usage patterns of bike stations depend on their immediate urban surroundings. Depending on the predicted demand, dock stations can be installed. Also, through improved forecasting of bike demand and inventory, ML can provide solutions to bike-sharing rebalancing problems, (where shared bikes accumulate in one location and are lacking in other locations).

Ashqar et al. (2017) modelled the availability of bikes at San Francisco Bay Area Bike Share stations using ML algorithms. Random Forest (RF) and Least-Squares Boosting (LSBoost) were used as univariate regression algorithms, and Partial Least-Squares Regression (PLSR) was applied as a multivariate regression algorithm. The station neighbours and the prediction horizon time were significant predictors for the model. To train the model, anonymised data on bike trips was collected from August 2013 to August 2015 in the San Francisco Bay Area. Data such as number of bikes available (at station i at time t,; number of available bikes in the neighbourhood at the same time), number of docks available, and time of recording the bike trips, station's ZIP code, and 22 other variables describing the daily weather for each ZIP code over two years were used as the main datasets.

Bike share can be made more efficient through site optimisation. Artificial Neural Networks (ANN) and genetic-algorithm-based optimisation models can be built to enhance the quality and efficiency of the bike sharing-service (done by selecting the right station locations). Some other algorithms used in the models for station site optimisation and demand prediction are K-Nearest Neighbour; Logistic Regression SVR with RBF kernel; CART; and Adaboost Decision Tree Regression (Liu et al., 2015). DL approaches can also be used in demand forecasting of station-free bike sharing, enabling the prediction of demand gaps (Xu et al., 2018).

Los Angeles Metro Bike Share and its partners have put together anonymised Metro Bike Share trip data which is accessible to the general public. Data such as start and end time, latitude/longitude coordinates and stations, plan duration, trip route category, bike type (standard or electric), etc., is shared regularly. This allows detailed analysis of travel patterns and distance preference. Such datasets can easily be used to train AI models efficiently.

Impact Assessment for India

The shift to non-motorised means of transport depends, to a large extent, on individual preferences. Its efficient usage could be an important feeder for public transport. But in India, due to the lack of appropriate infrastructure, the safety of NMT users is a concern. Cyclists and pedestrians are at maximum risk of traffic accidents in many Indian cities. Therefore, deploying AI for monitoring the infrastructure, efficiency, and working of NMT will influence and incentivise the users to shift to NMT for last-mile connectivity. Moreover, accurate information on the use of NMT, infrastructure availability, forecast of demand, and reallocation of resources will provide a solid foundation to make policy and infrastructure decisions, which will initiate a positive shift towards the use of NMT. The data on NMT infrastructure can be gathered through satellite imagery and crowdsourcing.

In India, comprehensive data on the use of NMT and its facilities is not readily available, though extensive research has been undertaken to examine its potential. Bike-share data on the availability of bikes, active docks and load is easily accessible but does not possess the relevant information to arrive at travel patterns such as the type of vehicle, planned duration, latitude/longitude coordinates, etc., which could be used to deploy suitable ML/AI tools. Here, for example, ML can provide tools and information for regulators to ensure that the bikes are not abandoned in public spaces and are dropped off at the nearest dock station post the ride.

Datasets along similar lines can be defined and captured for India to analyse and use NMT patterns, contributing towards informed policy decisions, awareness, and end-user impact.

Evaluation as per the framework: This use case of AI has the potential to build awareness and ensure effective policy enablement through data enrichment and augmentation as well as vulnerability assessment

4.1.2.2. Catalyse the shift to EVs

EVs have very low GHG emissions. The lifetime GHG emissions of electric cars registered in India in 2021 are 19-34% lower than those of petrol or diesel, or CNG cars (Bieker, 2021). Also, due to their small battery size and superior efficiency, electric 2-wheelers can enable a 20% reduction in GHG emissions (Abdul-Manan et al., 2022) .

As the shift to EV requires substantial behavioural change, interventions for nudging the appropriate behavioural change in consumers is critical. AI can be deployed in making decisions on the location of charging stations and for the optimisation of energy, routes, and charging, which will catalyse a pro-EV behavioural shift.

4.1.2.2.1. EV charging infrastructure

High opportunity | Mid to long term

A major factor influencing the decisions regarding shifting to EVs is the accessibility of EV charging stations. Setting up charging infrastructure is challenging, the location of the charging stations is very crucial and dependent on various dynamic factors such as the demand, grid capacity etc. AI plays a role in mapping potential infrastructure sites by employing techniques such as Graph Neural Network Random Forest (RF), Least-Squares Boosting (LSBoost), and Partial Least-Squares Regression (Li et al., 2021) aiding to data-driven planning of EV charging infrastructure.

A study on data-driven planning of electric vehicle charging infrastructure was carried out in Sydney, Australia. They used datasets on traffic flow and the corresponding distribution network (traffic volume and the transportation network) and economic activity from Sydney public transportation datasets. The dataset contains the traffic volume and the transportation network covering Sydney CBD and neighbouring suburbs. Vehicle volume count recorded at a frequency of one hour by sensors for the past 12 years, a very essential dataset, was easily available and accessible with New South Wales public service (Li et al., 2021).

For designing smart EV charging solutions at neighbourhood levels evaluation of household EV charging demand is a primary factor. Machine learning algorithms can be adopted to forecast the household day-ahead EV charging occurrence-time and the "no charge" day respectively. The combination of RF, NB, AdaBoost and GBoost algorithms can be used to predict households' EV charging demand (Ai et al., 2018).

Algorithms such as Pattern Sequence-based Forecasting (PSF), and SVR can predict the energy needs at a charging outlet for the next 24 hours aiding preparedness for the demand.

The usability of an EV largely depends on the state of the battery. To electrify routes it is necessary to understand if EVs can meet the necessary power and mileage requirements. The state of charge can be estimated with ML, by using subtractive clustering based neuro-fuzzy system (Adaptive Neural Fuzzy Interface System) approach. The energy consumption probability distribution (i.e. expected value and variance) for every road link in the road network can be predicted. By this, the amount of charge that will remain after the said trip can also be estimated (energy prediction), further trips can be planned and the potential for energy savings can be explored (Pelletier et al., 2019). Using information and datasets on the state of the battery, driver's behaviour, load and auxiliaries, the mileage of the EVs can be predicted through the Artificial Neural Network (ANN) model and the Multiple Linear Regression (MLR) model (Rabhi & Zsombók, 2022). By combining various battery-related prediction models and travel behaviour, routes which could be electrified can be identified.

ML can help in predicting degradation and usage using supervised learning techniques, fuzzy logic, and clustering. This information will help the users as well as the authorities in assessing the efficiency and also making sufficient arrangements for battery disposal and reuse strategies.

Evidence suggests that AI tools helps in balancing demand and supply of charging stations. The California Energy Commission, along with the Metropolitan Planning Organisations (MPOs) in California, funded the development of a planning tool called GIS UC Davis GIS EV Planning Toolbox. The tool suggests the location of the demand, based on market size and the magnitude of anticipated demand for the infrastructure given a market location. Based on the inputs, and market size, the tool gives the number of anticipated charging events and the number of kWh by location.

A similar tool was also developed by Field dynamics, a net zero data analytics consultancy in the UK called JumpStart. The tool helps local authorities to address the challenges involved while delivering EV charging infrastructure.

In Karnataka, India, the Bengaluru Electricity Supply Company (BESCOM) installed 136 public charging stations in the city in 2019-20, but the utilisation rate stands as low as 1 per cent. This is largely due to the positioning of these public charging stations. The BESCOM charging stations are invariably located inside government office premises, often inaccessible to EV users or unknown to them (Deshpande, 2021) .

Impact Assessment for India

Public charging stations provide a sense of security and psychological comfort to EV users, and encourage more people to switch to EVs. India is in the initial stage of EV penetration, which makes it the right time to plan, strategise, and develop its related infrastructure. AI/ML tools can prove to be very useful in providing data-driven information that can help in making informed decisions and planning the future.

In India, since the EV adoption rate is still not significant (with the total sale of EVs being only about 1% of total vehicle sales in India), essential datasets have not been captured to analyse the market size, anticipated demand, wear and tear of batteries, etc.

The need of the hour is to ensure that enough data is available and accessible, besides carrying out in-depth studies and research to assess the estimated demand and market size of EVs in India (which depends on consumer behaviour to a large extent, according to a 2022 CSTEP study). This would be possible only after substantial penetration of EVs in the Indian ecosystem. AI needs to be deployed to suggest the infrastructure needs as per the market size and magnitude of the demand in the country. Capitalising on this emerging investment opportunity will help realise the benefits to environment in terms of cutting down emissions, and also to the end user in the long run.

Evaluation as per the framework: This use case of AI has the potential to assist in effective policy enablement through various simulations and prediction modelling.

4.1.2.2.2. Energy efficient through optimisation

High opportunity | Immediate

Simultaneous charging of numerous EVs can lead to congestion in local power grids, resulting in potential overloading of both the cables and the transformers. Optimisation of the energy used by the EV through efficient routing and controlled charging to manage grid load is thus vital for the sustainable use of EVs.

Smart grid that uses AI can be a catalyst to increase the efficiency of the energy used (Rigas et al., 2015). To achieve energy efficiency, it is essential to have efficient EV routing and range maximisation. Algorithms and mechanisms have been developed to route EVs in order to minimise energy loss and maximise energy harvested during a trip. ML models such as the Ensembled model of SVR, RF, and DKDE can be employed to understand travel and charging behaviour, predict session duration and energy consumption. System dynamics such as future arrivals, departures, and energy consumption have to be known beforehand-, which can further be used to minimise load and queues at charging points.

This will avoid peaks and possible overloads of the electricity network, while minimising electricity costs. Efficiency can also be increased by utilising the storage capacity of EVs to balance the electricity demand of various locations in the network or to ease the integration of intermittent energy sources into the grid. Mechanisms and approaches have been developed to facilitate vehicle-to-grid energy transfer, and the potential of ML to improve such vehicle-to-grid technology is very high.

In 2018, UPS®—a global shipping and logistics company—introduced smart electric vehicle charging systems to power its central London delivery fleet It included an active network management system that monitored the required demand at the site and planned the vehicle charging by scheduling the charging sessions during evenings in a manner that allowed vehicles to be ready for the next day's delivery. Due to this system, UPS® could increase the number of electric trucks (7.5 tonne each) plying at its London site from of the earlier maximum (65 trucks) to 170 trucks, without requiring an upgrade in the power supply connection. Moreover, the company has also been able to increase its freight EV by 160% without upgrading the capacity of the local electricity network (UK Power Networks Services, 2020).

For avoiding the grid overload that results from charging too many electric vehicles simultaneously, a smart charging coordination system based on Reinforcement Learning (using an artificial neural network as a function approximator) can be considered (Tuchnitz et al., 2021). Under this, a central agent creates forward-looking, coordinated charging schedules for an electric vehicle fleet of any size, taking into account the baseload present in the power grid. According to the study by Tuchnitz et al., the Reinforcement Learning-based charging coordination system is shown to perform very well as compared to an uncontrolled charging strategy. All EVs possessed enough battery energy for their next trip on departure and charging was carried out almost exclusively during the load valleys at night. This novel charging coordination system offers a flexible, easily adaptable, and scalable approach for an EV fleet under realistic operating conditions.

The autoregressive integrated moving average (ARIMA) method can also be used for demand forecasting of conventional electrical load and charging demand of EV parking lots simultaneously. The model decouples the daily charging demand for EV parking area from the seasonally changing load profile, providing significant improvements in terms of error reduction (Amini et al., 2016).

Thus, optimisation and smart charging systems can avoid the need for an electricity network when the number of EVs (passenger and freight) increase, and can also avoid peak load on the grid.

Impact Assessment for India

India can also explore the possibility of using AI tools or write suitable AI/ML algorithms for energy optimisation.

EV penetration in India, especially of four-wheelers, is not very impressive. The penetration of heavyweight EV vehicles (like trucks, buses, etc.) is almost non-existent. Though the rate of penetration seems to be increasing in the case of two- and three-wheelers, there is a long way to go. The nature of datasets, i.e. the demand, charging pattern, load on the grid, etc. can also be obtained only when there is a substantial number of EVs plying on the Indian roads.

Thus, this AI use case has the potential to generate a positive end-user impact and mitigate climate change issues over the mid to long term. One of the factors for the low demand of EVs can also be the high purchase price of an EV for the consumer (CSTEP, 2022). Evaluating their costs versus overall returns in the Indian context will be useful in enabling informed decision-making by the end user.

Evaluation as per the framework: This specific use case of AI has the potential to derive end-user impact through processes and systems optimisation.

4.1.3. Modal shift

Shifting passengers/users to low-carbon-intensity modes is one of the most important ways of decarbonising transport. Interventions should be targeted towards promoting modal shift. To do so, individual travel information in an area and analysis leading to a better understanding of travel behaviour and demand patterns is crucial. The demand modellers and transportation practitioners can work with passengers' travel behaviour data based on which the travel plans and other decisions that will facilitate modal shift can be made. Along with demand and travel behaviour, there is a need to understand city traffic by collecting data, measuring the traffic, and analysing the current traffic situation. Since there is a complex interplay and network of interdependent factors and an abundance of data, AI/ML can be greatly leveraged here. Providing micro-mobility solutions to the passengers is an effective way of driving the modal shift of transport, for this AI approaches are most efficient.

4.1.3.1. Increase use of public transport

High opportunity | Long term

A shift from the use of private vehicles to public transport can result in a drastic reduction in GHG emissions. Interventions should be put in place to improve public transport, make it reliable to attract ridership and increase the satisfaction of transit users. Steps should be taken specifically to promote the use of public transport in Indian cities with focus on increasing electric public transport. According to a recent study by CSTEP (2022), if 30% of all passenger-kilometres in urban areas are electric, GHG emissions from urban passenger transport can reduce by ~ 10%.

Poor infrastructure, as well as congestion, adversely impacts the reliability and predictability of public transport. This can be addressed using AI, which can provide timely and accurate transit travel time information. ML methods along with real-time data can predict bus arrival times and their uncertainty. DL, when used to build data-based models and gauge the likely performance of a given transport network, will answer the following questions: how long will it take to travel on a certain bus route in a certain city at a certain time on a particular day of the week? What will be the halt duration of the bus at each station? How many passengers will the bus carry? What will be the arrival time? These AI models, if embedded into the scheduling optimisation engine, will give automatic suggestions for new and more efficient schedules.

By producing accurate travel time estimates, ML can provide tools that help in the coordination and integration of various modes of public transportation with others such as shared transport, NMTs etc. AI combined with optimisation algorithms allows optimising transit (various modes of transport) to improve on-time performance. Integrated transportation will help improve the existing public transport network, thus nudging citizens to move away from the use of private vehicles. ML and stimulation models can improve understanding and predict traffic behavior and travel patterns/modes in cities by exploring huge transportation data from roadways cameras, GPS, smartphones, traffic sensors etc., which can be used in informed transportation planning and formulate urban traffic mitigation strategies.

Electric bus fleets are being launched for public transport in cities like Bangalore. Here, AI can be deployed to estimate their driving range and increase the reliability of electric buses. Ensemble ML can estimate the driving range for electric buses by considering battery degradation levels. This will help the drivers and authorities to plan transportation effectively (Wang et al., 2021).

Global evidence suggests that AI applications backed with real-time data can increase the reliability of public transport system and improve passengers' dependency on them over the short to the medium term.

In the Netherlands, a regional public transport company utilised data regarding the occupancy of metros, buses, and trams. Based on the information gathered, the transport schedule for providing enhanced capacities/resources to travelers was generated. It also provided insight into possible capacity issues in the transport network when the number of travelers increases. Predictions of occupancy or available space in the public transport could be made for different time durations of the day and the transit schedule was molded accordingly. Moreover, bottlenecks in the increasing number of travelers were also identified and removed to prioritise network improvements. As a result, dependency on public transport increased gradually (KPMG, 2017).

Further, in a study by Organisation for Economic Cooperation and Development (2020), it was estimated that an increase in the share of passenger-kilometres by public transport from 8% to 33 % in New Zealand, would decrease greenhouse gas emissions by 40% by 2050 (due to the reduction in total kilometres travelled and a cleaner mode). The shift to public transport was immediate.

Impact Assessment for India

It is estimated that approximately 88 million trips in India are made through public transport daily, which translates into 6% to 9% of total trips being catered to by public transport, as against 30% to 35% in most countries across the world (KPMG, 2017). Clearly, the public transport facilities in India are not being utilised optimally. One of the reasons for the lack of active use of public transport could be below-par travelling experiences; absence of seamless intermodal travel, and integrated mass transit and feeder schedules; and lack of information pertaining to the capacity or occupancy of public transport, as well as unreliable services.

However, public transport data is not readily available in India. To derive a definite impact of this use case, sufficient data is required to assess the travel pattern of passengers and AI/ML tools to estimate/predict the driving range of public transport vehicles, transport schedules, available passenger capacities, etc. Moreover, as the decision to shift to public transport totally depends on individual preferences, the impact cannot be assessed with complete accuracy unless more research and studies are carried out to evaluate the preferences of the consumers or travellers.

Modal shift largely depends on consumer awareness and participation. Awareness about the ill effects of carbon and GHG emissions, and their climate change implication is necessary. But understanding individual contributions to carbon emissions and how they can be reduced is crucial for nudging a shift to low-carbon means of transport.

Further, the shift from an internal combustion engine (ICE) public transport vehicle to public EV could also be explored at a greater scale in the country.

Evaluation as per the framework: This specific use case of AI has the potential to derive end-user impact through simulations and prediction modelling, as well as processes and systems optimisation.

4.1.3.2. Shared transport

Uncertain

Urban mobility has also witnessed incidences of shared transportation. The use of AI-based technologies and intervention can further enhance shared mobility by providing reliable and essential information on demand and supply.

Drivers can easily access riders when ride-hailing or ride-sharing services are used. Swvl, an Egyptian start-up, developed a model that enabled creating of shared fixed-routes for buses depending on the number of riders headed in the same ML can also be used in understanding and predicting, if a customer decides to share a ride with other passengers from an on-demand ride service.

A study by Chen et al. (2017), employs the boosting ensemble learning approach for a better understanding of the ride-splitting behaviour of passengers. The goal of ensemble learning was to combine decisions or predictions of several base classifiers to improve prediction, generalisability, and robustness. The ride-splitting analysis is based on real-world city-wide on-demand ride sourcing data. Predicting ride-splitting demand can help optimise utilisation and rebalancing of assets, and increases the quality of available transportation services.

Access to timely and location-specific empirical analysis is crucial for decision-makers, to be able to know whether a ride-share service is diverting consumers from low-carbon transit modes and thereby increasing the use of cars. ML methods can help to understand the energy impact of shared mobility concepts which will help in informed decision making.

Various tools have been developed to calculate the carbon footprint for a given distance, mode of travel, type of fuel etc. AI can further strengthen this by predicting the potential reduction in emissions for individual trips if there is a shift from conventional vehicles to public transport systems or electric vehicles. This information can nudge behavioural change in users, and can also be useful for policymakers in making informed decisions.

Impact Assessment for India

Shared mobility is modifying the way people travel and think about vehicle ownership, and AI plays a vital part in running and optimising these services. Shared mobility can lead to optimum utilisation of resources (vehicles). *UberPool* claims to have saved 32 million vehicle kilometres travelled (VKT) since its launch in India in 2015.

But the impact of shared mobility on reducing GHG emissions is unclear. This is because shared vehicles can cause more people to travel by road. It could even get people to rely on services with high GHG emissions. Moreover, empty cabs or cab services offered during peak demand but running on the roads without any passenger carry the risk of adding mileage when travelling, which, in turn, negates the overall purpose of shared mobility to tackle climate change. Therefore, more studies and advanced research is required to assess the impact of this use case of AI.

Evaluation as per the framework: This specific use case of AI could assist in building awareness through different case-scenario simulations.

4.1.3.3. Autonomous vehicles

Moderate opportunity | Long term

The technology to enable vehicle automation or autonomous vehicles (AV) has emerged rapidly, causing much excitement and demand especially in the developed countries; its commercial use is quite less in developing countries. Globally, driverless vehicle-usage has the potential to lower traffic congestion and emissions contributing to climate change by 50 per cent or more by the year 2050, according to a 2017 report released by the Institute of Transportation Studies at UC Davis (ITS-Davis) .

AVs have the feature of eco-driving which is to increase energy efficiency and reduce energy consumption by reducing traffic congestion. ML is essential in the development of AVs, including basic tasks such as following the road and detecting obstacles. But some studies such as by Brown et al. (2014) and Wadud et al. (2016) also suggest that the energy use and the range of potential impacts of use of AVs are wide and uncertain. AVs that reduce travel cost and new traveller groups can lead to significantly more driving, faster driving, and increased use of high-energy-consuming features.

Impact Assessment for India

India, unfortunately, has to deal with the challenges of high congestion, lack of traffic lane discipline, and lack of the required infrastructure to support AVs. Making a self-driving car in India requires several million kilometres of real-world data, based on which an algorithm suited to Indian driving conditions can be created. This is a time-consuming and research-intensive exercise.

At present, no Indian automaker has announced plans of deploying AI technology anytime soon for local development of an AV. Even if created, there lies the risk of these AVs being potentially overwhelmed in highly congested driving environment in the country. They could also face a lack of demand from large sections of the Indian population due to their higher purchase price.

Further, AVs could fail to function well in the absence of smooth or developed infrastructure which is essential to normalise their running on Indian roads. Therefore, their sheer existence in the Indian market will depend on the nature of real-world data available, research to assess their suitability for the Indian travellers, consumers and the status of available infrastructure facilities for their smooth running.

Evaluation as per the framework: This specific use case of AI could assist in building awareness through different case scenario simulations.

5. AI for Water

India is home to 18% of the world's population, but has only 4% of its water resources, making it one of the most water-stressed country in the world (The World Bank Group, 2022). Further, there is ever-increasing demand for water, owing to the rapid rise in population and the growing economy of the country. In 2019, the Indian Council for Agriculture Research (ICAR) pointed out that the per capita annual water availability had reduced to 1,508 cubic meter in 2014 from 5,177 cubic meter in 1951. It is estimated to decline further—to 1,465 cubic meter by 2025, and to 1,235 cubic meter by 2050 (Press Information Bureau, 2019). Changing climate has a significant impact on water—direct and indirect—giving rise to complex social and economic challenges. Varying climate conditions alter the magnitude and intensity of rainfall, and groundwater recharge, leading to floods and drought disasters, salt water intrusion, and contamination of surface water and groundwater resources, placing the country's water resources under severe threat.

Between 1951 and 2015, the summer monsoon precipitation over India has decreased by 6%, with a major drop seen in the Indo-Gangetic Plains and the Western Ghats. Fall in surface water availability due to changing rainfall patterns increases dependency on groundwater. Due to over-extraction, and changing seasonality and intensity of rainfall, the groundwater levels have been receding at an alarming rate in many parts of India. A 2018 report by the NITI Aayog predicted that 21 cities—including Delhi, Bengaluru, Hyderabad, and Chennai—would run out of groundwater by 2030, affecting 100 million people and, more alarmingly, leaving 40% of India's population without access to drinking water. Water flow in the Indus, the Ganges, and Brahmaputra rivers is projected to fall by 8.4%, 17.6%, and 19.6 %, respectively, by the year 2050 (as compared to 2000 levels). This is attributed to declining rainfall as well as diminishing glaciers and snowfall in the Hindu Kush Himalayas.

Various studies conducted by the Indian Space Research Organisation (ISRO) have found that around 75% of the Himalayan glaciers are retreating at an alarming rate, causing variability in water flows to downstream areas (Prakash, 2020). Further, the arrival of anomalous (early) monsoon—when the glaciers melt—has resulted in large water quantity in the spring-summer months, causing flash floods.

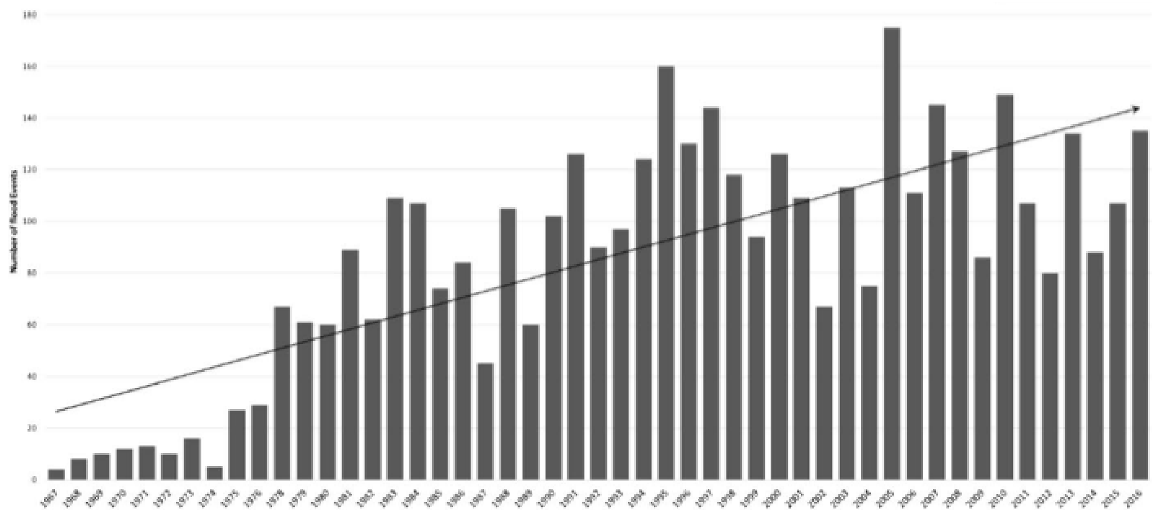


Figure 7(a): Temporal evolution of the number of floods

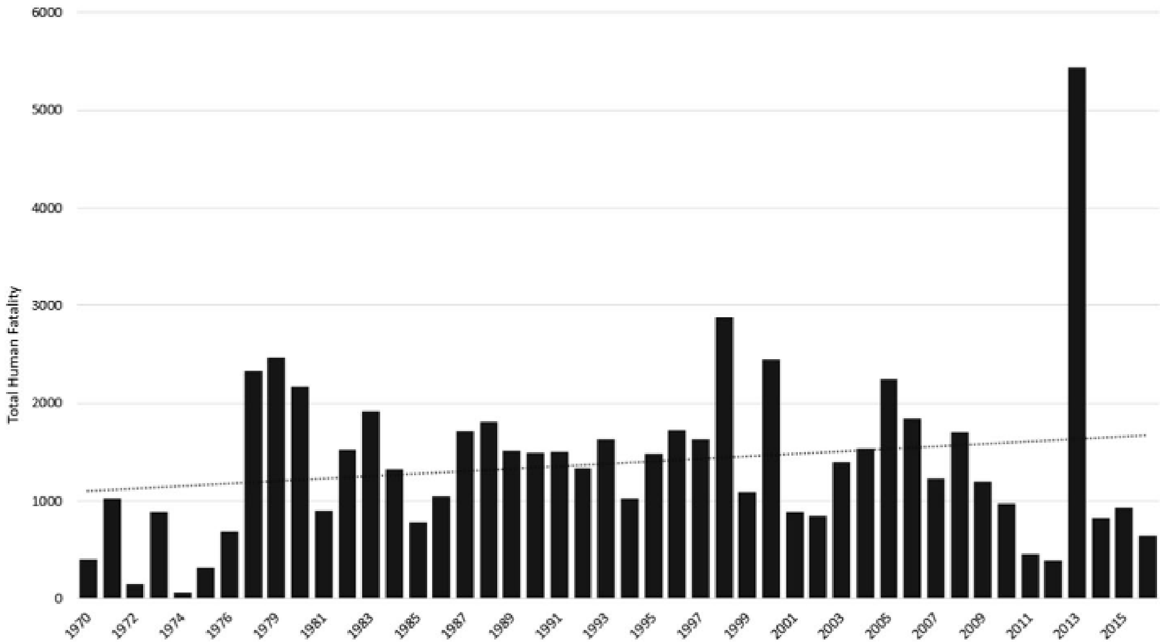


Figure 8(b): Number of flood fatalities on the national scale

Source: Indian Meteorological Department –Disastrous Weather Events sourced from Saharia et.al. (2021)

Climate variability has impacted the distribution of rainfall across the country in the recent years. According to IMD, India recorded 125 extremely heavy rainfall events during September and October in 2021, the highest in five years. There were 89 extremely heavy rainfall events recorded in September 2021 against 61 in the same month in 2021 and 59 in 2019. Floods are increasing in frequency and intensity. Floods contaminate freshwater supplies, heighten the risk of water-borne diseases, and create breeding grounds for disease-carrying insects. They also lead to loss of lives and livelihoods (deaths due to drowning, physical injuries, damage to houses, and deterioration in nutrition and health).

5.1. Water Management: Use Cases of AI

Owing to the complex interrelations between the various forms of water (surface and ground) and its various uses (drinking, industrial, agricultural, etc.), any intervention targeting one of the forms or uses is bound to have an impact on the other forms or uses.

The applications of AI in green economy, climate change, and sustainable development is becoming mainstream. According to the findings of the "Climate AI: How artificial intelligence can power your climate action strategy" survey by Capgemini Research Institute (2021), the average reduction in GHG emissions globally through use cases of AI in the utilities (electricity, gas, water) sector during the years 2018 and 2019 was the highest (nearly 14%) among all sectors. Further, the survey says that the AI use cases in the utilities sector are expected to bring about an average emission reduction of almost 16% over the next 2-3 years. The use cases in this sector can, thus, be instrumental in accelerating climate change adaptation efforts.

In this section, the identified use cases of AI in water management are examined using the thematic framework. Particularly, we identify the main AI-based approaches that can be utilised to make better decisions for water management and conservation, while enhancing service delivery and reducing costs. The impact assessment for each of the use cases has also been undertaken.

The use cases have been clubbed together on the basis of the areas in which the impact is created for adaptation, under (i) Glaciology; (ii) Integrated River Basin Management (IRBM); (iii) Ground Water Management, and (iv) Water Health Management.

A summary of all the use cases of AI in the water sector —along with their thematic framework evaluation, the necessary datasets required for their measurement, and their expected outcomes—is given in *Appendix II*.

Here we describe each one of them in greater detail, along with their potential impact.

5.1.1. Glaciology

Diminishing glaciers pose a long-time critical risk to water availability and security in India. Recognising the need for research in this area, the National Water Mission and estimated the cost of data collection on permanent and seasonal Himalayan snow to be close to INR 200 crores (Ministry of Water Resources, 2008). Climate-change-induced glacier collapse can lead to devastating flash floods in the downhill regions, like the one witnessed during in Uttarakhand in February 2021. Millions of people depend on the glacier- and snow-fed rivers of Indus, Ganga, and Brahmaputra. Changes in their volume and timing of flows will have devastating economic and social implications for the concerned region (The World Bank Group, 2021).

Himalayan glaciers covering the Indus, Ganga, and Brahmaputra basins were mapped by ISRO using Indian satellite data from 2004 to 2011. The mapping showed that there are 34,919 glaciers spread over 75,779 sq. km in the Himalayas. Further the advance and retreat of glaciers in the Himalayas were monitored in 2018 by ISRO using satellite data from 2000-2001 and 2010-2011. ICIMOD—an intergovernmental institute of eight countries—is working on adaptation in the Hindu Kush Himalayas (HKH) and provides baseline data on glaciers on a regular basis. This baseline data is generated semi-automatically using more than 200 Landsat 7 ETM+ images of 2005 (± 3 years) with minimum cloud and snow coverage (Cheng et al., 2021).

Deployment potential of AI in areas of glaciology

Given the centrality of the Himalayan glaciers for India, AI's can be deployed for the following:

- Frequent and more expansive monitoring of glacial retreat and advance
- Better estimates of glacial body mass changes (measurement)
- Estimations and predictions of other relevant glacial activities (e.g. glacial calving)
- Correlation of changes in glacial body mass to climate/weather patterns
- Simulation/estimates of glacial retreat under varying predictions of (long-term) climate conditions
- Better simulations/estimates of impacts of glacial changes in river water systems.

AI can augment research and studies in many of these areas. Research show that classification, feature spotting, automatic mapping, and visual interpretation tasks, as well as time series reconstruction and simulation, can be done through application of ML and DL (Taylor et al., 2021). The following diagram illustrates the potential AI applications for this domain.

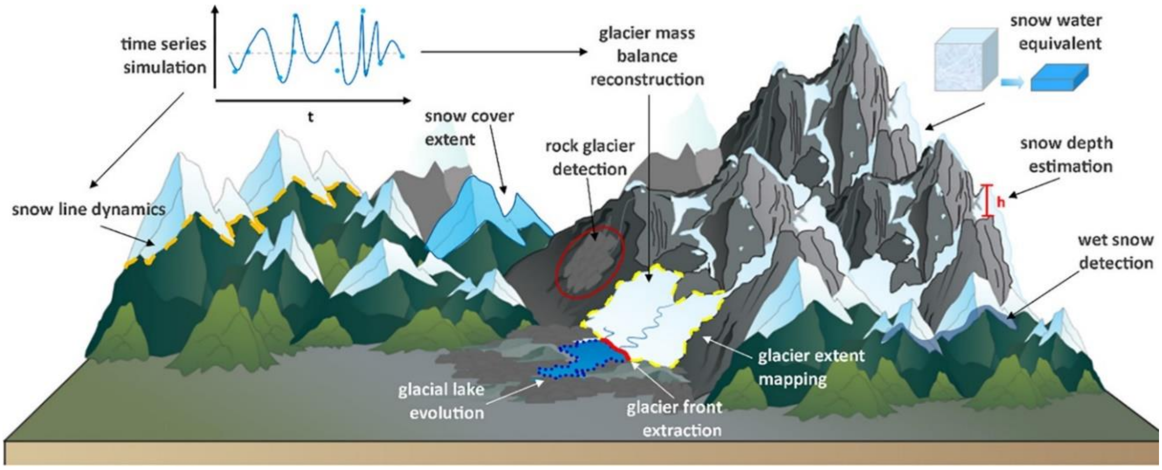


Figure 9: AI applications in glaciology
Source: (Taylor et al., 2021a)

5.1.1.1. Monitoring glacial changes

Glaciers are a source of freshwater but are continuously shrinking at an alarming rate. Their shrinkage has caused a rise in the current sea-levels and has led to frequent occurrence of floods. AI/ML or DL are needed to monitor the nature of glacial changes, estimate their impact, and plan the water resource management accordingly. This will, in turn, help in identifying and strategising ways to avoid risks and hazards associated with glacial body changes. This section covers (i) mapping glacier retreat; and (ii) estimating glacial body changes.

5.1.1.1.1. Mapping glacier retreat

High opportunity | Mid to long term

Embedding AI into sensors can create powerful tools for glacial monitoring. Hybrid models of DL and ML, which also have manually designed features, have led to improved techniques for snow-cover mapping (Taylor et al., 2021). The ML approach is based on algorithms such as semantic segmentation, while DL performs pixel-wise classification in images (U-Net architecture), gradient descent, and dice loss. Using data from satellite images can help in ecological monitoring of glaciers in the Hindu Kush Himalayas. By utilising readily available remote-sensing data, a model to identify and outline both clean-ice and debris-covered glaciers (with the help of satellite imagery) can be generated.

One of the easily accessible glacier mapping dataset that can be used to train AI models is the HKH dataset, which is organised by tiles. A tile is a spatial area measuring roughly 6 km x 7.5 km (with definitions that roughly match up with USGS quarter quadrangles). Each tile comes with one corresponding GeoTIFF file (Labeled Information Library of Alexandria: Biology and Conservation [lilawp], 2020). The entire glacier mapping dataset containing 35 tiles from some of the South and South-East Asian countries, including Afghanistan, Bangladesh, Bhutan, China, India, Myanmar, Nepal, and Pakistan, is available for use (Baraka et al., 2020). Similarly, AI tools have been used to model glacier thickness and volume (Haq et al., 2014).

Cheng et al. (2021) have employed neural networks to automatically identify the calving fronts of marine-terminating glaciers through decades of satellite imagery. A dataset of 22,678 calving fronts spanning 66 Greenlandic basins, from September 1972 to June 2019, was used in this study. Such an exercise can help in recognising and measuring the edges of glaciers in the satellite images of Earth's surface automatically and quickly, and reliably process numerous other glaciers, improving spatiotemporal coverage and accuracy of outputs.

5.1.1.1.2. Estimating the impact of glacial body changes

Uncertain

The existing literature on the subject underlines the nature of AI/ML tools used to estimate glacial body changes. For example, Min et al. (2019) use ML to predict ice flow techniques through unsupervised learning of future video-frame predictions for enhancing the precision of ice-flow tracking within multi-spectral satellite images. But future frame predictions of ice melt and tracking of ice-dynamics optical flow has modelling difficulties, owing to uncertainties in global temperatures changing precipitation patterns, occlusion from cloud cover, rapid glacial melting and retreat due to black carbon aerosol deposition from wildfires or human fossil emissions. The AI models with adversarial learning method, can be employed to further improve the accuracy of tracking the optical flow of ice dynamics. DL techniques have been used in the French Alps for data imputation (and filling in missing data) regarding glacial mass balance changes (Bolibar et al., 2022).

Floods are significant damaging disasters that put a huge burden of devastation on people. To minimise life and property damages from floods, forecasting of water levels of a flood-prone river is needed. A hybrid ML model of Adaptive Neuro Fuzzy Inference System (ANFIS) and Genetic algorithm, trained using data on temperature, precipitation, and water levels of the river, can be useful in forecasting the water level of glacial-fed perennial rivers. It can be improved further, when ANFIS models are optimised using the genetic algorithm (Imran et al., 2021).

Impact Assessment for India

In the Indian context, some glacier mapping datasets (like those on Hindu Kush Himalayas) are readily available. It is crucial to deploy appropriate AI, ML, or DL technologies to monitor or map the effects of climate change on the glacial structure, and assess the impact.

Also, comprehensive field or on-the-ground data are still not adequately available, owing to the inaccessibility to many glaciers. In these cases, data collected through drones and the Internet of Things can be useful.

<u>Evaluation as per the framework:</u> This specific use case of AI can assist in building awareness through data enrichment and augmentation.

5.1.2. Integrated river basin management

Integrated River Basin Management (IRBM) entails integrating the planning and management of water resources with sustainable development and strategies on a river basin level (Evers, 2016). The focus on Integrated Water Resources Management (IWRM) approaches has been growing with each new National Water Policy (NWP) in India. IWRM principles were envisaged as early as 1985 with the first NWP that emphasised using a hydrological unit (river basin) for planning and management. NWP 2012 stresses that IWRM will be at the core of water supply planning, production, and maintenance.

Under NWP 2012, a web-based Water Resources Information System (India WRIS) has been set up. This acts as a repository of nationwide water resource data, providing a "single window" source of updated data on water resources and allied themes. Sub-national level WRIS is also proposed to be introduced at state/UTs and river-basin levels.

Decision support systems like WRIS are some of the existing data foundations on which AI-based models and tools can be developed. There is immense potential to strengthen these systems through bidirectional relations with AI models on aspects like data collection, knowledge creation, and decision making.

Deployment potential of AI in areas under IRBM

The study examines various goals and aims of IRBM which are pertinent to India for climate change adaptation under the following three themes:

- Flood predictions and warnings
- Risk assessment (mid- to long-term) in terms of water availability (floods and droughts)
- Reservoir/multi-reservoir operations optimisation and water storage capacity planning

5.1.2.1. Predictions and risk assessment

The occurrence of devastating floods and droughts has been increasing in India over the years. These climate disasters have caused extensive loss of lives and livelihoods, and large-scale destruction of property and infrastructure. This calls for utilising AI for making prompt and accurate predictions of floods and droughts as well as for putting appropriate risk assessment measures in place. Forecasting the occurrence of disasters well in advance is crucial for taking the necessary adaptive steps. Disaster management is a key potential area for deploying AI to enable informed decision making and effective planning.

5.1.2.1.1. Flood prediction and warning

High opportunity | Immediate

The use of AI for predicting floods has gained popularity over the past decade. Approaches like Multi-layer Perceptron Neural Networks (MLP-NN) and Adaptive Neuro-Fuzzy Inference System (ANFIS) have been used to forecast the river level for different lead times. Wavelet decomposition (Wavelet Neural Net) and Ensemble Prediction Systems (EPS) have also been widely used (Mosavi et al., 2018). A decade's hourly water data was used to train the forecasting models. This increased the accuracy and time range of prediction for flood warnings. Interestingly, in most models, the lead time of prediction considered is hourly or daily, with very few attempting a prediction based on a time horizon of a week or more (Nur Adli Zakaria et al., 2021).

Research on assessing AI deployment in flood forecasts and predictions is being conducted in various academic institutes in India. For instance, multiple studies have been carried out for the Mahanadi Basin, using and comparing various techniques. A study on the rivers Brahmaputra and Ganga shows that the use of HydroNets—a deep neural network model designed to exploit both basin specific rainfall-runoff signals—and upstream network dynamics, lead to improved flood predictions at longer time horizons. The injection of prior knowledge on the river structure reduces sample complexity and allows for scalable and more accurate hydrologic modelling, even with a few years of data (Moshe et al., 2020).

Impact Assessment for India

Flood predictions are based on real-time, large data sets, with the solution being scaled to cover most river systems in India. While some work is already being carried out in this field in India, more research efforts are needed to extend the solution or develop new models in areas (especially the coastal regions) where gauge measurement and other meteorological data are sparse (Nevo, 2020). AI-based flood predictions and forecasts can be enabled over the short-run, provided the necessary data and information is available.

Evaluation as per the framework: This use case of AI can help in effective policy enablement and bring end-user impact through various simulations and prediction modelling.

5.1.2.1.2. Risk assessment – floods and droughts

High opportunity | Mid to long term

AI can predict fluvial floods by measuring runoff changes in rivers, while meteorological droughts can be measured using the Standard Precipitation Index (SPI). Approaches such as Convolutional Neural Network (CNN), Long-Short Term Memory network (LSTM), and Wavelet decomposition functions combined with the Adaptive Neuro-Fuzzy Inference System (WANFIS), along with flood and drought indicators, can forecast floods and droughts in both arid and tropical regions (Adikari et al., 2021).

A flood-risk assessment framework that combines flood susceptibility assessment and flood consequences (human health and financial impact) can be built using AI tools and geospatial data, which, in turn, can help in developing a flood-risk assessment map. Hybrid artificial intelligence models integrated with multi-criteria decision analysis are also efficient. According to a study by Pham et al., (2021), two hybrid AI models, namely AdaBoost-DT (ABMDT) and Bagging-DT (BDT) were developed with Decision Table (DT) as a base classifier for creating a flood susceptibility map. A total of 847 flood locations of major flooding events and 14 flood influencing factors of topography, geology, hydrology, and environment were used to construct and validate the hybrid AI models. The flood susceptibility map produced by the model, when combined with a flood consequences map, produces a reliable flood risk assessment map, which can be used for better flood hazard management, helping government and agencies minimise the damage caused by floods.

Recent research showcases the use of ANN models that are trained with data on Precipitation Condition Index (PCI), Vegetation Condition Index (VCI), Temperature Condition Index (TCI), and Soil Condition Index (SCI) derived from multi-source remote sensing satellite imagery. These models have helped in drought risk assessments and predictions in Maharashtra. The outputs of such models can help plan targeted initiatives by state and local governments in the region(Singh et al., 2021).

In a research study for Ethiopia AI was successfully used in geospatial analysis. A GIS-ANN model was trained with data on flood-causing factors such as rainfall, slope, elevation NDVI, K-factor, R-factor, river distance, geomorphology, road distance, SPI, and population density (Tamiru Dagne & Dinka, 2021).

Impact Assessment for India

Risk assessment requires many overlapping sets of data such as those on flood predictions combined with flood consequences, Vegetation Condition Index, Temperature Condition Index, and infrastructure details, etc. Data collection is getting tedious as climate changes and precipitation and rainfall-runoff pattern variations become more extreme. Consequently, accurate training data for making assessments is becoming scarce. Once the datasets and the necessary information are available, the risks can be determined or assessed by deploying the appropriate AI-based tool. The overall benefits from the assessment can be realised in the short to medium term.

This use case of AI would entail an assessment of not only the nature of climate change but also the associated risks involved, to enable informed decision-making.

<u>Evaluation as per the framework:</u> This use case of AI can help in effective policy enablement through various simulations and prediction modelling and risk and vulnerability assessment.

5.1.2.2. Reservoir operations optimisation

High opportunity | Short to mid term

AI solutions can be used to optimise reservoirs across a river basin. These models have the capability to optimise water flows and its release from dams to take care of dam safety, prevent flooding, and mange power generation, and environmental and water availability goals. Preparing forecasts on water loss and final reservoir storage is vital for optimising reservoir operation. Good forecasts would lead to better management of flash floods and water crisis problems. ANN prediction models with radial basis function (RBF) are noted to have high efficiency and accuracy, especially in the dynamics system. Based on the climate conditions, evaporation from a reservoir can also be predicted. Datasets, such as daily pan evaporation and mean air temperature over a decade, are required to build the model, using algorithms such as radial basis function neural network (RBF-NN) and support vector regression (SVR) (Allawi et al., 2019).

Water scarcity mitigation and flood defence can also be done effectively through streamflow forecasts. Multi-step streamflow forecasting that can determine the optimal water allocation on the basis of current use, as well as the carry-over storage needed for mitigating water scarcity risk in the future, is crucial for current reservoir operations. AI-based management methodology that integrates multi-step streamflow forecasts and multi-objective reservoir operation optimisation for water resource allocation can be used here. Various combinations of climate and hydrological variables are used for AI-based modelling, such as a long-short-term memory (LSTM), a gated recurrent unit (GRU), and a least-squares support vector machine (LSSVM). These can forecast short-term streamflow and plan storage (Guo et al., 2021).

In South Korea, hybrid models have been used to improve forecasts of daily water levels in the Andong dam watershed (Seo et al., 2015).

Impact Assessment for India

The use of AI-ML hybrid models for controlling and managing reservoir systems can be effective in assessing water levels and the associated risks. In India, supporting evidence for the successful use of AI hybrid models for optimisation of reservoir operations is scarce. Also, good forecasting is critical for ensuring the effectiveness of reservoir operations, water supply, flood prevention, hydropower generation, and water resources management. Forecasting and optimisation of reservoir flow can give vital information for policy design and infrastructure planning. The information could also be useful to mitigate operational hydrology complications arising from the change in precipitation characteristics, overpopulation, urbanisation, industrialisation, and change in farming practices. Since this use case of AI is largely dependent on the right hybrid mix of modelling and forecasting, it could be supplemented with other use cases to derive reliable and reasonably accurate information.

Evaluation as per the framework: This use case of AI can help in effective policy enablement and create end-user impact through processes and systems optimisation.

5.1.3. Managing groundwater levels

Since groundwater is easily available in India, its overuse for both irrigation and drinking purposes is rampant. The Central Ground Water Board (CGWB), based on an assessment in 2020 estimates that about 16% of groundwater blocks are overexploited (ground-water extraction is exceeding the annual replenishable groundwater recharge). The total ground water extracted of the entire country for the year 2020 has been estimated as 244.92 billion cubic meter (bcm). Further, 89 % of total annual ground water extracted is for irrigation purposes, while the other 11% is for domestic & industrial use (Central Ground Water Board, 2021). Current overexploitation rates pose severe threats to livelihoods, food security, climate-driven migration, sustainable poverty reduction, and urban development. For example, cropping intensity may decrease by 20% nationwide and by 68% in groundwater-depleted regions (Jain et al., 2021).

Rapid groundwater depletion affects the flow of rivers and streams, disturbing the entire aquifer ecosystem. The pre-monsoon groundwater level in India declined by 51% between 2016 and 2019 (Central Ground Water Board, 2020). The natural recharge of groundwater determines water availability. Since climate change directly affects the groundwater recharge cycle, mainly by altering rainfall patterns, it is crucial to continuously monitor the groundwater levels, so that necessary measures and regulations can be taken. AI may be used in different ways to monitor the depletion in groundwater levels. It can also help in mapping groundwater potential, monitoring its quality, and checking the rate of recharge.

5.1.3.1. Mapping groundwater zones and estimating recharge rate

High opportunity | Mid to long term

Optimising the use of groundwater resources by striking a balance between consumption and recharge is extremely essential. To take measures for adequately recharging the aquifer, mapping the groundwater potential sites is necessary. Hybrid AI methods, along with GIS, can be used for groundwater potential mapping. Modified RealAdaBoost (MRAB), bagging (BA), and rotation forest (RF) ensembles with functional-tree- or FT-based classifier are some approaches for potential mapping (Phong et al., 2021) .

As mentioned earlier, precipitation is the principal source of groundwater recharging. Accurate knowledge of the recharging rate is essential for most groundwater-related studies and projects, especially in water scarce regions. AI approaches can estimate the recharging rate of groundwater, thus helping in evaluating the sustainability of groundwater supplies. Recharge rates forecasting would be immensely beneficial for groundwater resource management and aquifer recharge. The key datasets required include the recharging rate of the soil or ground surface, and environmental input characters, which are used for training models using Gaussian process (GP), M5P, and random-forest- or RF-based regression methods (Sihag et al., 2020).

Hybrid AI models were used for groundwater potential mapping in Vietnam (basaltic terrain at DakLak province, Highland Centre), which helped in water resource management and allowed the country to maintain the balance between consumption and exploitation.

Impact Assessment for India

Mapping of groundwater potential is the need of the hour in India, but is not being undertaken effectively at present. Hybrid AI models can be explored in this area. Also, the deployment of AI for recharging groundwater is essential and should be immediately pursued as the rate of recharge determines the level or extent of groundwater sustainability. Predictions on potential groundwater zones and recharging rates will provide evidence and more information for targeted monitoring, effective resources usage, and informed policymaking. Suitable policies in this area will enable effective groundwater management and the benefits of this specific use case of AI is expected to be realised over the medium to long run.

<u>Evaluation as per the framework:</u> This use case of AI can help in effective policy enablement through risk and vulnerability assessments, as well as through sensing, monitoring, and risk detection techniques.

5.1.3.2. Precision farming

High opportunity | Mid to long term

India's agriculture sector consumes 85% of the country's available freshwater resources. With rapid population growth and the resultant increase in food demand, the consumption by this sector is rising continuously. There is, thus, a need to come up with more efficient technologies to ensure prudent use of water resources for irrigation. Precision farming, which optimises water usage, can be an ideal option for conserving this valuable resource. For undertaking precision farming, the input parameters about the soil -- such as moisture content, temperature, and nutrient content of soil--, meteorological data, and information on weather forecasting is essential. This would require an array of advanced tools and technologies, such as field sensors, soil sensors, drones, satellite imagery, GPS, GIS, and IoT devices, to analyse data. An automated robotic model for the detection of moisture content and temperature can be built to predict the amount of water required. Dielectric method, Time Domain Reflectometry (TDR), PLSR, and other egression algorithms are some approaches used to detect moisture content of the soil and supply water according to the requirement (Talaviya et al., 2020).

Impact Assessment for India

The use of AI in the area of farming holds promise. AI can reduce crop cost, increase crop yield, and save water resources. However, the majority of farmlands in India are fragmented, resulting in non-availability of data from remote areas and farmlands that don't meet the minimum hectare criteria. Comprehensive data collection in this area may, therefore, be quite ambitious. Precision farming requires the available AI technology to be implemented in all farms, apart from a large physical infrastructure. This involves heavy investments. The adoption of precision farming in India is still in the nascent stage mainly due to the unique pattern of land holdings, poor infrastructure, lack of farmers' inclination to take the risk, and various social and economic issues.

Evaluation as per the framework: This particular use case of AI can help in effective policy enablement and capacity building, and create end-user impact through processes and systems optimisation, informed decision-making, and upskilling of farmers.

5.1.4. Managing water health

Indian cities are growing and expanding at unprecedented rates, facing critical impediments like pollution, loss of ecosystems, resource degradation, inadequate infrastructure, poverty, and unemployment. The risks posed to urban centres by climate change are increasing alarmingly as well. Climate variability has increased the frequency of extreme weather events, one of which is urban flooding. While untimely heavy rains can be attributed to climate variability, urban flooding is largely due to the unplanned urbanisation of Indian cities. It is largely a man-made disaster caused by overburdened drainage, unregulated construction, and a clear disregard for the natural topography and hydro-geomorphology.

The Indian Smart Cities Mission gave a considerable fillip to efforts for leveraging technology-based solutions for urban water management. The key area of focus in these projects has been on reducing Non Revenue Water (NRW). On an average, NRW in Indian cities is estimated to be as high as 40% to 50% (Japan International Cooperation Agency [JICA], 2014). Simple technology interventions in the form of sensor networks have yielded results in some cities. For example, Nagpur has employed a combination of 24X7 water supply and smart water meters, which has helped the city in reducing its NRW (ET Government, 2019). Similarly, Chandigarh and Pune have started shifting to a smart meter-based system for water distribution (INDIAai, 2020). More recently, the nation programme "Atal Mission for Rejuvenation and Urban Transformation (AMRUT) 2.0" launched in 2021—which aims to provide water supply, sewerage, and urban transport to households, and build amenities in cities—emphasised on making cities water secure and leveraging the latest global technologies for this (PIB, 2021). AI intervention has yielded results in urban water management in India and abroad. Flood forecasting and warning, management of drainage systems and city waste, monitoring encroachment of flood plains, etc., are areas where AI can play a key role.

5.1.4.1.Urban flood prediction and management

High opportunity | Immediate

Metros, and Tier I and Tier II cities are bearing the major brunt of rapid urbanisation. The unplanned urbanisation often leads to drastic alterations in the drainage characteristics of natural catchments or drainage areas, due to excessive volume and rate of surface runoff during rains. In Bengaluru for instance, extreme and unpredictable rainfall events, alongside unplanned urbanisation, have considerably increased the risks of urban floods in low-lying areas in the city over the past few years.

Similarly, cities like Hyderabad and Mumbai rely on a century-old drainage system, which covers only a small part of the core catering to a small population. While increased volumes of drainage water and blockage of drains due to indiscriminate disposal of solid wastes makes it difficult for the existing drainage systems to cope, redesign and construction of urban drainage networks is prohibitively expensive. . Therefore suitable models that can predict risk of flooding, along with the locations and severity of floods, are urgently required.

AI can be employed to develop Data Driven Models (DDMs) to predict urban flooding in real-time, based on weather radar and/or rain-gauge rainfall data. ANN can be configured for prediction of flooding at manholes on the basis of rainfall input. It can also be used to now-caste rainfall, based on the relationship between radar data and the recorded rainfall history. These two ANNs can then be cascaded to predict flooding in real-time, based on weather radar. Urban floods can also be forecasted by predicting total accumulative overflow in an urban drainage basin. A study done in Korea used Deep Neural Network to predict the total accumulative overflow, based on Storm Water Management Model (SWMM) simulations, and used data augmentation to increase the input data. The SWMM was a one-dimensional model for rainfall-runoff analysis. Data on statistical characteristics of each rainfall event was used as input data, which was available with the Korea Meteorological Agency (Kim & Han, 2020).

The CENTAUR (Cost Effective Neural Technique to Alleviate Urban flood Risk) system developed by the University of Sheffield uses AI to control floods in a city. The AI-based system uses fuzzy logic—a way of interpreting uncertain conditions, such as the actual water level—to make decisions. Pilot installations of AI-based flood management systems have proven successful in Portugal (Sykes., 2019), and France (Mujumdar et al., 2021).

Impact Assessment for India

In the case of urban areas, predicting increased water levels in the urban drainage systems on the basis of weather and other influencing factors would help in taking necessary precautions, both by the local bodies and citizens. A pilot study by Mujumdar et al., (2021) was conducted to develop a model for predicting floods in the low-lying areas of Bengaluru city. A network of automatic rain gauges (ARGs) and 25 water-level sensors (WLS) were installed across Bengaluru. These sensors recorded water-level data continuously and transmitted it to a server at a temporal resolution of 15 minutes. The data was used for validation of the model and to examine its success. The pilot model used real-time rainfall data for predictions and forecasting. Such models can be developed for other Indian states as well. However, to assess the end-user impact in the short to medium term, advanced research is required in this field.

Evaluation as per the framework: This particular use case of AI can help in effective policy enablement and derive end-user impact through simulation and prediction modelling, as well as sensing, monitoring, and risk detection techniques.

5.1.4.2. Reducing non-revenue water by optimising water distribution networks

Moderate opportunity | Long term

NRW refers to water that has been lost due to leakage, physical losses, theft, metering inefficiencies, etc., before reaching the end user. Water networks show considerable heterogeneity with regard to control structures, management strategies, etc., as they experience continual expansion and changes in water demand. Due to these characteristics, water distribution companies face problems in integrating data and knowledge integration related to control and optimal usage. In most cases, there is no suitable model of the networks and their behaviour, because of which the control and supervision strategies are based on manual procedures, and some heuristic rules. Water distribution networks, therefore, are a promising application domain for machine learning. A study was conducted by Camarinha-Matos & Martinelli (1999) to apply ML techniques in the framework of the European project WATERNET. The technique had a supervision system, a distributed information management subsystem, an optimisation subsystem, a water quality monitoring subsystem, and a simulation subsystem. In addition to these components, a machine learning subsystem was included to understand the networks through historical data and thus improve the performance of the water management system. For ML training, historical data was collected through sensors, and the actions performed on the actuators by a Portuguese water distribution company (that has 45 water stations), were used.

Global case studies show that AI can be used to detect patterns and leakage in city water systems, and to highlight anomalies with smart networks. This can help detect leaks and save on the time and resources invested in reducing NRW (United Nations Development Programme, 2020). An Israeli company *Utilis Israel Limited* has developed algorithms to analyse imagery from satellites to detect the signature of drinking water leaking underground(Maccioni, 2019).

In India, a pilot project was developed by Indian Institute of Science(IISc), which uses data analytics and ML to identify the complex water distribution network in Bengaluru, with the aim to examine the inequities in water distribution, and generate evidence-based recommendations to resolve them (IMPRINT India, n.d.).

Impact Assessment for India

In India, the concept of NRW is not well known. Moreover, there is not sufficient evidence to suggest the extensive use of AI in the management water distribution networks. One of the reasons for this could be the lack of necessary data (water supply companies often provide unstructured and incomplete data related to network, control systems, water stations, network operations, etc.). Also, independent data collection involves considerable time, manpower, and cost, owing to the complex nature of water networks in Indian cities. Advanced and in-depth research needs to be carried out to study the complex and heterogeneous water distribution networks across Indian states to assess the real impact of the AI use case.

Evaluation as per the framework: This use case of AI has the potential to derive end-user impact through processes and systems optimisation.

5.1.4.3.Monitoring loss of water bodies and water quality

Uncertain

Water resources in urban areas are gradually decreasing due to rapid urbanisation, and encroachment of wetlands, floodplains, etc. Obstructions in floodways also cause loss of natural flood storage. To protect water bodies, urban planning today requires accurate information on extraction and automatic identification of water bodies (e.g., rivers, lakes, canals, and ponds). AI and ML can play an important role in enabling authorities to effectively monitor, as well as stop the encroachment of water bodies in urban areas. In a study by Huang et al. (2015), a novel two-level machine-learning framework was used to identify the water types through urban high-resolution remote-sensing images. The framework consists of two interpretation levels: (i) water bodies were extracted at the pixel level, where the water/shadow/vegetation indexes were considered; and (ii) water types were further identified at the object level, where a set of geometrical and textural features were used. Both levels employ machine learning for image interpretation. The framework was validated using the GeoEye-1 and WorldView-2 images. The results achieved satisfactory accuracy for both water extraction and water type classification in complex urban areas, thus helping in monitoring changes and preventing loss in urban water bodies.

Urbanisation, encroachment of water bodies, frequent flooding, blocked sewage, etc. result in contamination both surface water and groundwater. Deteriorating water quality in urban areas is also an important issue for which AI can develop possible solutions. Modelling and predicting water quality have become extremely important for controlling water pollution and providing enabling authorities to make informed decisions. Advanced AI algorithms have been used to develop water quality index (WQI) and water quality classification (WQC). In a study by Aldhyani et al. (2020), ANN models, namely nonlinear autoregressive neural network (NARNET) and long short-term memory (LSTM) deep learning algorithms, were developed to predict WQI. Further, machine learning algorithms such as support vector machine (SVM), nearest neighbour (K-NN), and Naive Bayes, in combination with water data from across India were used for WQC forecasting.

Similarly, private companies have also created AI applications to assess water quality. 'Clean Water AI' is an application that uses a DL neural network and computer vision to detect dangerous bacteria and harmful particles in water. Using the application, drinking water contamination can be seen at a microscopic level with real-time detection (Shanthi, 2021). However, more research and studies are needed to assess the effectiveness and accuracy of such AI applications.

For the study by Aldhyani et al., datasets containing 1679 samples from different states in India for the period of 2005 to 2014 were used to train the models. The dataset had seven significant parameters, namely, dissolved oxygen (DO), pH, conductivity, biological oxygen demand (BOD), nitrate, faecal coliform, and total coliform. Data were collected to assess the quality of supplied drinking water. However, the accuracy of such models depend on the quality of data and the extent of data availability. The more comprehensive the data, the better the level of accuracy. In a similar study by Haghiabi et al.,(2018) in Iran, AI models were trained with datasets with a sampling timeline of more than 55 years including measurement parameters like temperature (T), bicarbonate (HCO_3^{-1}), sulfates (So_4^{-2}), chlorides (Cl), total dissolved solids (TDS), sodium (Na^+), magnesium (Mg^{+2}), calcium (Ca^{+2}), thus enhancing the accuracy of predictions.

Impact Assessment for India

The assessment of water quality in India requires comprehensive and accurate data to enable proper predictions. Therefore, the impact of this AI use case is dependent on the availability and accessibility of sufficient suitable data. India can deploy AI to develop remote-sensing imagery to retrieve and monitor urban water bodies across its cities, which will provide information and insights for informed decision-making and effective policy enablement. However, this will also depend upon the nature of data or information available. In other words, building an effective water monitoring system depends on extensive availability of data sets and research findings.

Evaluation as per the framework: This particular use case of AI can help in effective policy enablement through simulations and prediction modelling, as well as build awareness through various sensing, monitoring, and risk detection techniques.

6. Roadmap for the Future

The previous sections have described the potential and impact of AI use cases for climate change mitigation and adaptation, specifically in the transport and water sectors of India.

As we approach the final sections, it is imperative to address a critical question: how can the relevant stakeholders and audiences (from the government sector, academia, research institutions and think tanks, industry, civil society, media groups, etc.) leverage AI's climate action potential to the optimum level? For this, a clear and well-defined roadmap to best align the use of AI with India's climate change mitigation and adaptation pathways has been included in this report. This roadmap for the future includes (i) a Climate Action Matrix that can help identify and prioritise the potential use-cases of AI for climate action; and (ii) a set of concrete policy recommendations to push for and guide the large-scale deployment of AI in India's climate change mitigation and adaptation efforts.

6.1 Climate Action Matrix

The Climate Action Matrix—which positions each AI use case (in the transport and water sectors) according to its potential opportunity and the expected ease of implementation in India—will enable stakeholders to prioritise areas of climate action. As such, it provides the way forward for climate action.

The Matrix is divided into four quadrants, with each quadrant indicating a certain level of potential opportunity presented by a use case and its ease of implementation in India. Each use case of AI mentioned in the study for the transport and water sectors is assessed and distributed accordingly in the Matrix. Such evaluation will also help in identifying the potential or future climate action opportunities that can be leveraged in India in the near to long term, with the help of AI.

As shown in Figure 9, in the Matrix, the x-axis shows the potential opportunity of the AI use cases and the y-axis shows the expected ease of implementation. The Matrix is defined through the four quadrants: I, II, III, and IV.

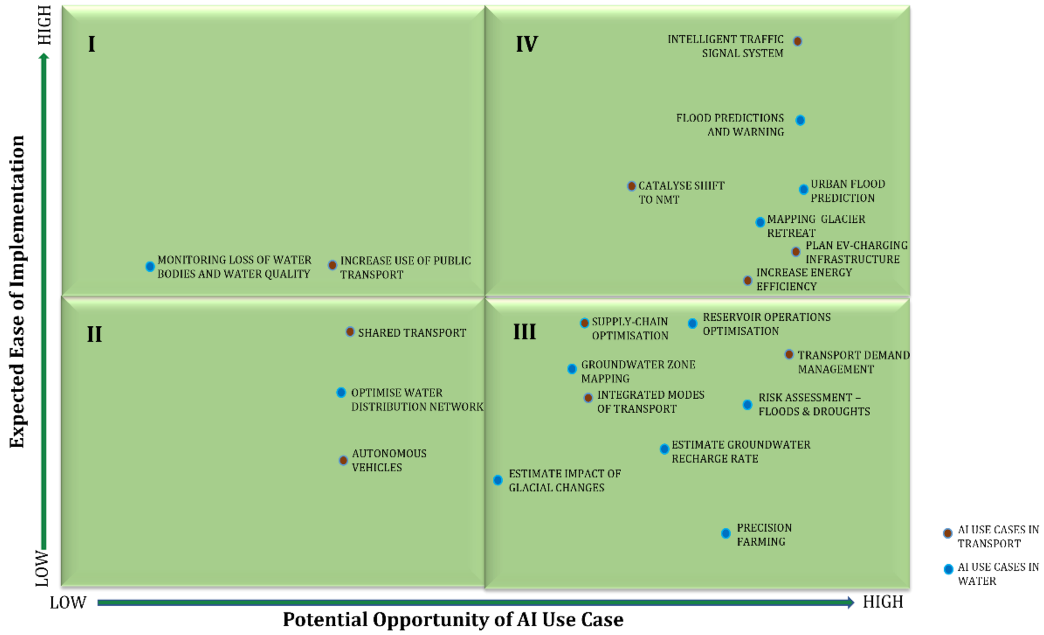


Figure 10: Climate Action Matrix

The I[st] quadrant includes use cases with a not-so-high (potential) opportunity that can be leveraged in India with greater (expected) ease of implementation; the II[nd] quadrant includes use cases with a not-so-high opportunity and a not-so-easy implementation process; the III[rd] quadrant includes those that have high potential opportunities but low ease of implementation; and the IV[th] quadrant includes use cases that have a high level of both potential opportunities and ease of implementation.

Thus, according to the Matrix, depending on their ease of implementation, the use cases in the III[rd] and IV[th] quadrants should be prioritised in India to capitalise on their high opportunity potential. In other words, the use cases of AI in these quadrants can be leveraged first as their benefits are expected to outweigh the costs of their implementation in the long run.

6.2 Policy Recommendations

India is witnessing a phase where the use of AI to tackle climate change issues is just beginning to pick up serious momentum. Moreover, considerable work is already underway in some of these fields. For example, studies and mapping of glacier advances and retreats in the Himalayan region are being carried out, and pilot-scale experiments are being conducted to forecast and assess the risks of floods in river basins, urban areas, etc. Similarly, in the transportation sector, considerable research has been undertaken in India to assess the benefits of EVs.

Considering that some concrete efforts are being made towards utilising AI for climate good, the time is apt to strive for extensive deployment of AI for climate action across the various sectors in India. **The right policy push—backed by a robust data infrastructure and active community participation—would be instrumental in achieving this.**

We present a set of **policy recommendations and suggestions** below to guide the relevant stakeholders and target groups in enabling AI's effective deployment for climate change adaptation and mitigation in India on a large scale.

Align climate change strategies with (regulated) AI-enabled solutions and vice-versa

A cohesive climate action strategy must include 'responsible AI' capabilities for sustainable development. Similarly, tackling climate change must be an integral part of AI's overall vision for addressing today's transformational challenges to meet the sustainability goals.

- It is critical to **leverage AI's potential in the climate action space**. Therefore, any plan or vision on climate change (at the national, state, or an organisational level) can consider the possibility of including technology-driven solutions through AI. It is imperative to **embed AI in the overall national and business strategies and vision on climate change as well,** to also ensure that the AI projects on climate change progress from the pilot stage to the prototype stage and ahead, and do not get stalled at the pilot stage itself. **Digital innovation pathway initiatives could be designed** to scale up successful pilot projects to the next level and beyond.

- Similarly, it is necessary to **include the adverse climate impacts resulting from the use of AI, while framing regulations regarding AI application in all sectors,** to ensure its responsible and effective use in adaptation and mitigation strategies.

- AI-driven technologies also carry the risk of having an adverse or negative impact on climate change sometimes. Therefore, it is **imperative to use tools or approaches to measure and monitor the carbon footprint of AI**. In other words, **regulating the emission impact of AI use cases** must be explored. Further, the use cases of AI must be deployed under manual supervision to ensure that the benefits of AI deployment exceed its cost of emissions. If need be, **regulations can be imposed regarding mandatory disclosure of GHG emissions**, energy consumption, etc. **that result from the use of AI technologies.**

- **Suitable regulatory sanctions and economic incentives** could also be explored by the policymakers to promote the use of environment-friendly AI deployment in the country.

Develop a comprehensive data infrastructure and enable data sharing

The success of AI use cases in tackling climate issues depends upon the availability, as well as the accessibility of sufficient and relevant data.

- The absence of a data-driven culture is one of the major challenges in adopting AI for climate change. To tackle climate change with the help of AI, a data-driven and scientific approach is needed.

- There is also a need to allow for greater data democratisation and access to reliable data, so as to allow the relevant researchers, climatologists, policymakers, thought leaders, and technologists to use it for predictions, forecasting, analyses, modelling, etc.

- The public or the private sectors could be invited by the regulator to host data, develop suitable data platforms, data licensing mechanisms, and processes to include feedback from stakeholders etc. to enhance their in-house data implementation capacities.

- Besides, it is also imperative to establish suitable data standards and protocols for data sharing. Data portals, data reserves, or data banks that can be linked to or interfaced with other portals (having common standards) could be explored.

- Setting up a dedicated or nodal regulatory body, committee, or data-driven task forces in climate-critical sectors could also be explored in India to oversee the data collection and sharing activities, provide data support and accessibility to the relevant stakeholders, and guard against any unscrupulous or unethical events. The Energy Data Task Force of the Government of the United Kingdom (UK) is a good reference. The task force has been formed to modernise the UK energy system and lead it towards a "net-zero carbon future through an integrated data and digital strategy throughout the sector" (Global Partnership on Artificial Intelligence et al., 2021).

- India could also explore the possibilities of collaboration with other countries for developing open-source climate-relevant data, strategies for AI deployment, technology simulations, etc.

Set up suitable physical infrastructure

The right physical infrastructure will serve as the foundation for sustainable AI-enabled solutions.

- Physical infrastructure that addresses climate challenges is very important for the effective functioning of AI algorithms and models. For example, in the case of the transport sector, the availability of sufficient EV charging stations will eventually spur the demand for EVs in the country. At the same time, AI could be used to optimise the use of EV charging points by determining the household EV charging demand, predicting the energy needs at a charging station, managing the charging time, enabling route efficiency, managing the load on the power grid, identifying areas for the development of interconnected grid, etc. Managing the load on the grid is crucial for maintaining a steady electricity supply and avoiding overload on the electricity network, which can be done through interconnected electricity grid systems. Similarly, the availability of interconnected grid systems could help in sharing the peak load of power stations, thereby balancing the grid load. Therefore, **AI can help optimise the energy requirements with the help of supporting physical infrastructure.**

- The scope of AI's applicability depends primarily on the availability of large datasets. This, in turn, requires the provision of suitable physical technology tools or technology infrastructure in most cases. For e.g., sensors and remote-sensing tools are needed to gather data on soil quality, nutrient content, etc. for precision farming. Therefore, the **right policy push to develop the necessary physical infrastructure for supporting the effective deployment of AI is vital.**

Build capacity and promote R&D and information dissemination

AI-for-climate literacy, skills development, and awareness building are key prerequisites for widespread community participation.

- Climate change is not the responsibility of a single institution or stakeholder; rather it is a collective effort of all sections of the society. There is a need to bring about a change in the mindsets and attitudes of Indian citizens for greater and sustainable AI adoption. Therefore, educating and building awareness among the masses on how AI can make a real difference in resolving the climate crisis is essential. This can be done by organising virtual and physical campaigns regularly in the urban, semi-urban, rural, and semi-rural areas.

- At the same time, there is a need to facilitate, and fund if needed, multidisciplinary teachings and applied research in AI-for climate-relevant fields, in schools, colleges, and higher education institutions (HEIs). Besides promoting digital literacy, relevant educational curricula on topics such as 'intersection of AI and climate change', technical, socio-technical components, data collection and curation methodologies, entrepreneurship skills, etc. can be included in the national education system.

- Investment in R&D is essential. R&D programmes specifically designed to understand the technical readiness of AI for climate change adaption and mitigation can be initiated at the HEI and national scientific research institutions.

- Availability of special research grants and funding for innovative projects, especially those that are directed towards innovative AI-for-climate solutions, will provide the much-needed fillip to R&D and innovation in this field. Further, suitable funding and investment options can boost the start-up culture and encourage new ventures and innovations in this field in India.

- Workshops, and training and curated sessions at the workspaces can enable upskilling or reskilling of the workforce/employees with the necessary expertise in this field. Capacity building is critical for climate action.

- Information and data collection can be encouraged through crowdsourcing, which uses the collective wisdom of a crowd to find the solution to a problem that affects the crowd. Through crowdsourcing, a large group of dispersed population can contribute in collecting the required data (normally sparse data) or scattered information. It can be widely used for tracking real-time data on rainfall, traffic congestion, etc., which could, in turn, be used for analyses and forecasting with the help of AI.

Encourage community participation, partnerships, and collaborations

Community participation and strategic collaborations are a smart way to deliver AI-for-climate goals effectively.

- Partnerships and collaborations promote knowledge exchange and shared pooling of resources. Therefore, multi-sectoral collaborations or consortiums involving diverse expertise from the government, academia, and industry are essential to foster an AI-enabled climate action ecosystem. This can also help in bridging the government-research-institution gap as well as the academia-industry gap.

- Besides domestic partnerships, the possibility of international collaborations must be explored with relevant global agencies to pool data; develop standards of data-sharing; bring together researchers and innovators to address common climate issues; enable exchange of best practices, policy designs, and cross-border technology solutions; and develop AI-for-climate solutions. This can help in meeting the climate goals efficiently and also in developing effective climate-related policies.

- Adequate incentives and encouragement from the domestic or national regulatory bodies in the form of collaboration-driven funding opportunities, tax incentives, market exclusivity (especially for the private sector), etc., can be beneficial in leveraging strategic business deals and long-term partnerships in the AI-for-climate-action space.

7. Conclusion

Climate change is threatening the world with food and water scarcity, deteriorating human health, and endangered lives and livelihoods. In India, extreme climate events (such as floods, cyclones, and heat waves) have caused widespread damage and human suffering over the past few decades. The impacts of climate change are likely to grow exponentially, with disproportionate consequences for the marginalised communities. Therefore, the coming years are crucial for climate action, in terms of effectively responding to, as well as preventing the highly damaging impacts of climate change. This mandates accelerating mitigation and adaptation efforts by embedding innovative tools like AI/ML within the climate action strategies across various sectors. With a host of promising opportunities for application across sectors, AI can play a big role in strengthening the ongoing efforts in this area. While the impacts may be visible immediately or in the long run, the steps to utilise AI in the climate action space need to be taken right away.

This study is a first-of-its-kind initiative for a comprehensive assessment of the role and impact of the use cases of AI for climate change mitigation and adaptation in India. The roadmap provided under the study guides the stakeholders in prioritising the areas for implementing these use cases, and also recommends the ways and means to align AI better with the national climate change strategies. Such a roadmap is of vital importance, given that the manner in which the relevant audience and stakeholders choose to deploy AI in the near future will significantly impact India's progress towards achieving its climate action goals and commitments.

However, leveraging AI's full climate action potential in India would require contributions from across the society, spanning communities, institutes, and governments, especially those working in the area of AI for climate good. As such, their meaningful involvement in the country's AI-for-climate action pathways and strategies is indispensable.

Also, the availability of structured datasets is a vital pre-requisite for the progress of AI for climate action, as algorithms learn from the datasets to analyse, optimise, or make predictions. Appropriate policies to encourage data collection, as well as to protect data would need to be brought in, and an infrastructure to host public datasets with ease of data transfer would need to be set up by the government with the involvement of all stakeholders.

Considering that the momentum is set and steadily gathering pace in the country in this important field, CSTEP shall continue to direct its efforts towards reinforcing the need for responsible AI for climate action in India.

8. References

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Appendix I

Use cases of AI that can be deployed for climate change mitigation in the transport sector

Use cases that lead to reduced transport activity			
S. No.	**Description of Use Cases and Datasets Required**	**Thematic Evaluation of Use Cases**	**Expected Outcomes**
1	**Intelligent traffic signal system** This is based on real-time traffic to optimise traffic flow and road infrastructure utilisation. **Type of datasets required**: • Number of vehicles for a given time interval at an intersection, the overall traffic flow, and rerouting options. • Queue lengths and the queuing time. • Information on influence of weather conditions.	**End-user impact**: Optimisation of processes and systems through real-time traffic capture and analysis, and video analysis.	• This will lead to a reduction in vehicle idle time and increase motor efficiency. The information is used to adjust signal timing for an intersection or group of intersections to improve traffic flow, including allowing platoon flow through the intersection.
2	**Management of transport demand** • Understand the transport demand in terms of routes, timings and mode. • Identify ways to maximise usage of transport on a particular route. **Type of datasets required:** Travel patterns, public transit users, demand, public transport routes, congestions, and topology.	**Policy enablement** • Data enrichment and augmentation. • Simulations and prediction models.	• Demand modelling and planning new infrastructure can significantly shape decisions on how long trips are planned and which transport modes are chosen by passengers/people.
3	**Supply chain optimisation**	**End-user impact**	• AI can enable organisations to take supply decisions effectively and account for uncertainties in multiple areas

	Optimising urban freight delivery travel to reduce emissions **Type of datasets required:** Freight details (number of packages, load, type etc.), delivery details, current demand, traffic information, and road networks.	Optimisation in process and systems	such as supplier management, demand forecasting, predicting arrival, thereby identifying and planning around transportation disruptions. • Scalability is possible but implementation will depend on infrastructure and support/acceptance from e-commerce players.
Use cases that lead to clean transport transition			
4	**Infrastructure assessment for non-motorised mobility** Assess the infrastructure for seamless connectivity at major nodes and transport hubs by crowdsourcing satellite imagery. **Type of datasets required:** • Multi-factor features extracted from human mobility, station network structures, and location. • Transportation-related features such as walking distance from each NMT station to its nearest transport hub, NMT routes, frequencies of trips in the different trip distances and time intervals, etc.	**Policy enablement and awareness building** • Data enrichment and augmentation • Vulnerability assessment	• AI algorithms will identify the gaps in infrastructure that hinder the use of NMT for last-mile connectivity. This will help authorities understand and prioritise infrastructure, which will promote NMT. • Scalability depends on public awareness and participation.
5	**Location/ geographical decisions for electric vehicle charging plug-ins** Decision-making tool for local public charging stations, grid analysis, predicting demand zones, and optimising utilisation of chargers, as well as grid. **Type of datasets required:**	**Policy enablement** Simulations and prediction models	• It will enable local authorities to realise the true scale of the challenge ahead of them and model potential infrastructure sites that align with their overall goals. • This framework can allow a multi-criterion analysis to identify more feasible locations and related requirements.

	Traffic flow and the corresponding distribution network (traffic volume and the transportation network), economic activity, residential charging patterns.		
6	**Optimising energy efficiency of the existing EVs and electric freight vehicles** Use of algorithms for energy-efficient EV routing, congestion management, and integration of EVs into the smart grid. **Type of datasets required**: State of Charge (SoC); current grid baseload (i.e. the load from households without EV charging); energy needed; the charging decisions already made for other EVs; the number of currently connected EVs; number of electric vehicles at home (i.e. number of private EVs); vehicles' arrival time; travel duration.	**End-user impact** Optimisation of processes and systems	• It will help in optimising charging time by understanding the electricity-usage pattern over the period. AI can help improve energy efficiency, avoid peaks and overloads in the electricity network and also explore vehicle-to-grid algorithms. It can also help in introducing discriminatory pricing based on peak timings. •
7	**Assessing the usage of EVs in inter-city freight** Trips that could be electrified can be identified based on the state of the battery, mileage offered, route, total daily run required, halt time, availability of charging infrastructure, etc. **Type of datasets required:** Battery state of charge (SoC), driver behaviour, load and auxiliaries, actual power loss, available and requested power, road links, and road nodes.	**Policy enablement** Simulations and prediction models	• AI can predict energy consumption for various trips based on battery and route information. Along with the information on the available energy, trips that can be electrified, could also be identified.

Use cases that lead to modal shift			
8	**Increased reliability and predictions of public transport** Assess the existing public transport network; provide timely and accurate transit travel time information to attract ridership; and increase the satisfaction of transit users. **Type of datasets required**: Real-time traffic data, routes, vehicle information, driving patterns, road conditions, weather condition data, number of battery-driven electric bus (BEB) being driven, and data on number of charging points.	**End-user impact** Simulations and prediction models.	• It will help in predicting the performance of a public transport network by giving accurate information based on real-time data, making public transport more reliable and user-friendly.
9	**Integrated modes of transport** Based on live information and predictions of millions of people travelling in a city (using multiple modes of transportation), AI can enable planning and running mass transportation networks. **Type of datasets required:** Travel pattern, real-time traffic data, routes, modes of transit available, vehicle information, driving patterns, road conditions, data on weather condition, number of BEB being driven, and data on number of charging points.	**End-user impact** • Simulations and prediction models. • Optimisation in process and systems.	• Deploying AI will help manage route planning and schedules in real-time, predict transportation demand, and ultimately orchestrate all the different types of transportation in a given city. • It will also help in identifying gaps in the transport network in fulfilling the predicted demand and integrating various modes of transit.
10	**Predictions to increase the number of shared rides** • Prediction for ride-splitting behaviour of passengers to help provide prearranged and on-demand transportation service.	**Awareness building** Case scenario simulations.	• It can help understand vehicle-sharing behaviour and predict passengers' decision to opt for a shared ride or shared vehicle (which will reduce demand). This will require trends of shared mobility in India as well as the global trend to estimate future scenario.

	• Analyse the energy impact of share rides-both private and public. **Type of datasets required**: Trip-sharing data such as time and location of each stop, vehicle type, preference, and GPS position of each trip data, data on the weather condition.		• AI can also help understand the energy impact of shared rides and also help optimise shared rides for vehicle efficiency (based on the pick-ups, final destination, etc.)
11	**Estimations of reduction in emissions** • A tool to estimate emission reduction potential for individual trips due to a shift from conventional mode of transport to electric vehicles or public transport system. • AI-based tools are not yet being used in India. Manual models are being developed and used by individual organisations **Type of datasets required:** Data and information on local travel patterns, mode of transport, fuel, distance; information on the conventional mode of transport and emission factors.	**End-user impact** Sensing, monitoring, risk detection.	• Will motivate people to shift to cleaner and sustainable transport. • Largely depends on public awareness.
12	**Autonomous vehicles** Driverless vehicles which increase energy efficiency and reduce energy consumption. **Type of datasets required:** Several million kilometres of real-world traffic data, and data related to traffic rules, road conditions, and weather.	**Awareness building** Case scenario simulations.	• Driverless vehicle usage has the potential to lower traffic congestion and GHG emissions from vehicles.

Appendix II

Use cases of AI that can be deployed for climate change adaptation in the water sector

Use cases that have an impact on floods and droughts			
Glaciology			
S. No.	**Description of Use Cases and Datasets Required**	**Thematic Evaluation of Use Cases**	**Expected Outcomes**
1	**Monitoring glacier retreat** • Measure the current rate of glacier recession in the Himalayas through image processing. • Estimate glacier recession/diminishment under varying Climate Change Conditions. **Type of datasets required**: Datasets required on glacial termini, glacier mapping.	**Awareness building** Data enrichment and augmentation	• AI neural network is capable of recognising and measuring the edges of glaciers in satellite images of the Earth's surface. It will increase the frequency and extent of monitoring and lead to greater automation in glacier mapping. It will also build technology and capacity for long-range forecasts of climate impacts.
2	**Estimation of impacts of glacial body changes on rivers** • Establish AI-based image processing techniques to recognise/estimate various glacial phenomena which can impact the flow of water into rivers. • Improve and expand the model to better estimate changes in snowmelt, which is a part of the river water systems on a long-term basis. **Type of datasets required:** Data on snow, ice on land, ice caps, glaciers, permafrost, and sea ice. Rate of ice melt and the optical flow of ice.	**Policy enablement** Risk and vulnerability assessment	• Builds technology and capacity for long-range forecasts of climate impacts on rivers. This will help in an accurate and dependable simulation to underpin informed long-term adaption and mitigations policies, including food security and agriculture in north India. • Builds alternative 'water availability paths' following climate paths to assess issues of water availability under various degrees of global warming.

Integrated River Basin Management (IRBM)			
3	**Improved flood predictions** • Flood warning (including flash floods)/short-term prediction systems based on currently observed weather patterns. **Type of datasets required:** Data on hourly water level, and weather conditions.	**End-user impact** Simulations and prediction models	• Prevents the loss of lives and livelihoods. It will also lead to increased accuracy of forecasts, longer warning times, and minimally gauged rivers. • Models for very short-term predictions, both traditional and AI-based already exist and are under further development – especially for river basins. Need to enhance models for hilly regions and improve warning time.
4	**Flood risk assessment** • Enhance models for flood risk assessment in the river basin and coastal areas under climate change conditions by integrating estimated/potential changes in rainfall, early snowmelt, and, extreme weather events. **Type of datasets required:** Meteorology data, geospatial data, water levels in the basin, events affecting water levels, infrastructure information.	**Policy enablement** Simulations and prediction models Risk and vulnerability assessment	• Estimates risks of flooding in coming years and prevents damage to lives, livelihoods, and property and infrastructure. • Provides inputs/guidance to develop resilience plans for infrastructure, and resilient planning of investments in new infrastructure; improves the accuracy, and decreases the cost of risk assessment.
5	**Optimisation & integration of reservoir operations** • Tool to plan the storage capacity and simulation of water flow of reservoirs w.r.t short-term weather forecasts to manage dam safety, flooding, environmental hazards, power systems, and other water availability goals. **Types of datasets required:** Inflow, water release of the dam, initial and final storage of the reservoir, weather conditions, and rainfall.	**Policy enablement and end-user impact** Optimisation of processes and systems.	• Enhances manual judgment and operations with short-term what-if simulations, and provides structured risk assessment modelled on expected rainfall. The goals are to prevent flooding even under low-probability extreme event conditions and plan and manage reservoirs.

Use cases that have an impact on depleting groundwater levels			
Groundwater Management			
6	**Predicting levels and mapping groundwater zones** • Tool to map potential zones where groundwater is available and to predict the levels of groundwater under varying rainfall and extract levels. **Type of datasets required:** Data on geo-hydrology of groundwater wells, topographical and geo-environmental factors, water consumers or users (such as agriculture sector, industry, etc.).	**Policy enablement** Risk and vulnerability assessment	• Prediction and accurate mapping of the groundwater potential zones will help in adequately recharging the aquifer for optimum use of groundwater resources by maintaining the balance between consumption and exploitation.
7	**Estimate rate of groundwater recharge** • Models to estimate the localised groundwater aquifer recharge. This will help in addressing groundwater recharging in urban and rural areas at the micro-level, and also in efficient management of resources. **Type of datasets required:** Topography, local geo conditions, local weather conditions, time, sand, clay, silt, bulk density, and moisture content.	**Policy enablement** Sensing, monitoring, and risk detection	• Understanding the recharge rate of a groundwater aquifer will help in managing the water availability, the rate of extraction, etc. • Helps in making important decisions regarding life and infrastructure around the aquifer, as the recharge rate depends not just on the rainfall levels but also on soil recharge rate, infrastructure, etc.
8	**Precision farming** • AI/IoT-based tools for better or optimised crop planning and irrigation schedule, thereby improving agricultural productivity.	**Policy design, awareness building, and end-user impact** Optimisation in processes and systems; informed decision-making, upskilling	• AI-powered solutions improve quality and ensure a faster go-to market for crops. The data on moisture content is gathered to give suggestions on water used. • The usage of AI in conjunction with IoT solutions for precision

	Type of datasets required: Data on historical meteorology, soil reports, moisture content, weather conditions, rainfall, insect infections, crop information.		farming is well understood and well developed, ultimately leading to improved agricultural yields, rise in farmers' incomes and overall development of the agriculture sector.
Use cases that have an impact on water health			
Water Health Management			
9	**Urban flood prediction** • Storm water management models can predict the overflow in urban drainage basins, thus predicting the probability of urban floods. • Models can also be employed to predict urban flooding in real-time based on weather or rain-gauge rainfall data. **Type of datasets required:** Data on rainfall, combined sewer sub-network, weather conditions.	**Policy enablement and end-user impact** Simulations and prediction Models Sensing, monitoring, and risk detection	• Data-driven models will provide accurate predictions on urban floods, thus providing opportunities for policymakers to take appropriate action. • Also provides information to local bodies and citizens to take preventive and precautionary measures before the floods hit.
10	**Optimisation of water distribution networks** • ML can be applied to develop a system to control and manage water distribution networks. **Type of datasets required:** Data on water distribution companies, networks, and water stations.	**End-user impact** Optimisations in processes and systems	• Reduces water leakage and water contamination in urban distribution systems.
11	**Prevent the loss of water bodies** • Monitoring of urban water bodies through image processing.	**Policy enablement** Simulations and prediction models	• Generates evidence, accuracy, and the capacities to continuously monitor water losses. Also, helps prevent encroachment. • Useful for areas with acute groundwater depletion

	Type of datasets required: Data on remote-sensing imagery of urban areas.		(will prevent further depletion).
12	**Monitor water quality** • Use image processing on water samples to monitor the quality of water for contaminants. **Type of datasets required:** Data on dissolved oxygen (DO), PH, conductivity, biological oxygen demand (BOD), nitrate, faecal coliforms, total coliforms, etc.	**Awareness building** Sensing, monitoring, and risk detection	• Reduces the cost of water quality monitoring by reducing the requirement of special devices/human specialists. Highly relevant as 70% of surface water in India is contaminated. (Microsoft AI is currently funding such projects).

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