GSMA

Combatting forest fires with AI in Pakistan

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Authors and contributors

Authors: Nigham Shahid (Senior Insights Manager, GSMA Mobile for Development) and Lauren White (Insights Analyst, GSMA Mobile for Development)

Contributors: Daniele Tricarico (Senior Director, GSMA Mobile for Development)

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Acronyms and abbreviations

AI	Artificial Intelligence
AKAH	Aga Khan Agency for Habitat
CCTV	Closed-Circuit Television
CDA	Capital Development Authority
DFO	District Forest Officer
DL	Deep Learning
DRM	Disaster Risk Management
DRR	Disaster Risk Reduction
EFCCC	Ethiopian Environment, Forest and Climate Change Commission
ESA	European Space Agency
FIRMS	Fire Information for Resource Management System
GHG	Global Greenhouse Gas
ICT	Islamabad Capital Territory
IoT	Internet of Things
IWMB	Islamabad Wildlife Management Board
KP	Khyber Pakhtunkhwa
LIMS	Land Information and Management System
LoRaWAN	Long-range, Wide-area Network
LUMS	Lahore University of Management Sciences
MHNP	Margalla Hills National Park
ML	Machine Learning
NASA	National Aeronautics and Space Administration
NDMA	National Disaster Management Authority
NOAA	National Oceanic and Atmospheric Administration
PDMA	Provincial Disaster Management Authority
PTZ	Pan Tilt Zoom
SOP	Standard Operating Procedure
SUPARCO	Space and Upper Atmosphere Research Commission
USF	Universal Service Fund
VIIRS	Visible Infrared Imaging Radiometer Suite
WWF	World Wildlife Fund

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Definitions

Algorithm A process or set of rules to be followed in calculations, especially by a computer, to solve a problem.

Artificial intelligence Artificial intelligence (AI) is comprised of widely different technologies that can be broadly defined as “self-learning, adaptive systems”.[1] AI has the capability to understand language, solve problems, recognise pictures and learn by analysing patterns in large sets of data.

Computer vision Computer vision is a type of AI that enables computers and other machines to identify and interpret visual inputs from images and videos.[2]

Deep learning Deep learning is a branch of AI that enables machines to mimic the way a human brain learns, through neural networks. Large sets of data are processed in three or more layers: an input layer where data is entered; hidden layers where it is further transmitted, shared and processed; and an output layer where a final result or outcome is reached, enabled by a predefined set of steps or instructions (algorithm).

Machine learning Machine learning is a subfield of AI, broadly defined as the capability of a machine to imitate intelligent human behaviour and learn from data without being explicitly programmed.[3]

Remote sensing Remote sensing is acquiring information from a distance via remote sensors on satellites, aircraft and drones that detect and record reflected or emitted energy. All objects on Earth reflect, absorb or transmit energy, with the amount varying by wavelength. Researchers can use this information to identify different Earth features as well as different rock and mineral types.[4]

1 Definition by the International Telecommunication Union (ITU). See: Artificial intelligence for good.
2 Definition taken from Microsoft Azure’s dictionary on cloud computing.
3 Definition by the MIT Sloan School of Management, based on the definition by AI pioneer Arthur Samuel.
4 Definition by NASA Earthdata.

Executive summary

Climate change is having a direct impact on the frequency and severity of natural disasters, including floods, earthquakes and wildfires. Escalating global temperatures are causing hotter, drier conditions that contribute to more forest fires. These fires wreak havoc on both wildlife and human settlements, with a disproportionate impact on the world's most vulnerable populations.

The emergence of artificial intelligence (AI) is proving to be increasingly valuable in forecasting natural hazards like forest fires and detecting natural disasters in their early stages. This allows government departments and agencies to act quickly to prevent and alleviate the impact of such disasters, both by deploying additional resources and first responders to high-risk areas and by issuing early warnings to communities before the situation escalates. Increasingly, AI is being used for more precise damage assessments following natural disasters, facilitating a more targeted response.

Although the use of AI in natural disaster mitigation is still nascent, it is expanding rapidly, reinforcing existing disaster risk management (DRM) systems. However, the effectiveness of AI in predicting, detecting and responding to disasters hinges on the availability of data. Effective AI deployments also require institutional capacity, stakeholder coordination, sustainable financing and community inclusion.

Pakistan is a country particularly susceptible to natural hazards due to its high temperatures, arid landscape and geographical location, which make it prone to floods, earthquakes and forest fires. Despite contributing less than 1% to global greenhouse gas (GHG) emissions, the country ranked 8th in the Global Climate Risk Index in 2021 and faces substantial impacts from climate change.[5] In 2018 (the last available measurement of poverty in Pakistan) the World Bank estimated that 40% of the population was living below the poverty line, and projected this would decline to 37.2% by 2023.[6]

Historically, forest fires in Pakistan have been low intensity, but the devastating Sherani fire in 2022 resulted in loss of life and inflicted significant economic costs on local communities that rely on the commercial sale of pine nuts.[7] It is estimated that more than 900,000 pine nut-bearing trees – the key source of income for local communities – burnt in a blaze that took 13 days to extinguish. This is estimated to result in a loss of PKR 4 billion (USD 18.6 million) per year for many years to come, as these trees take between 25 and 40 years to regenerate and produce enough pine nuts for commercial harvest. Pakistan's forest management system, a holdover from colonial times, relies predominantly on inadequate human and financial resources to predict, detect, manage and respond to forest fires. In the event of a high-intensity fire outbreak, Pakistan would struggle to protect communities and wildlife adequately.

Strengthening Pakistan's forest fire management system by integrating emerging technologies such as AI holds immense promise for mitigating the occurrence and escalation of fires and averting catastrophic events such as the Sherani fires. By leveraging AI algorithms, the system can analyse extensive datasets on conditions conducive to forest fire outbreaks, enabling accurate predictions of both outbreak risks and the trajectory and intensity of ongoing fires. Moreover, AI-powered image analysis can swiftly detect fires, bridging surveillance gaps in remote and under-patrolled regions and curtailing their spread in the early stages.

By adopting a more technology-centric approach, Pakistan can significantly reduce the frequency of forest fires and facilitate early detection. This would relieve the strain on overstretched forestry departments and enhance their resource management capabilities, mitigating risks from natural hazards more effectively and safeguarding ecosystems and communities from the devastating impacts of wildfires.

To build an enabling environment and develop capacity to bolster the existing forest fire management system with AI, Pakistan would benefit from undertaking the following actions, that also apply in other contexts aiming to develop an AI-enabled system.

5 German Watch. (2021). Global Climate Risk Index 2021.
6 World Bank. (2023). Poverty and Equity Brief: Pakistan.
7 Saeed Khan, R. (19 September 2022). "Long term impacts of 'terrible' fire season in Pakistan's mountains". PreventionWeb.

Strategic priorities for effective AI-enabled forest fire management systems

Prerequisites	Action	Actor
Better co-ordination between key actors involved in forest fire management	The public sector, in the case of Pakistan federal and provincial disaster management authorities, need to align more closely to establish a shared vision and objectives of an AI-enabled disaster risk reduction (DRR) system and their role in its development.	**Disaster management authorities**
	Public and private sector organisations and academia must proactively collaborate with each other on data collection and sharing, technology development and deployment, and algorithm development, based on their particular strengths and capabilities.	**Data partners** **Technology partners** **Disaster management authorities** **Universities with Engineering and Computer Science departments**
	Disaster management authorities, forestry departments and emergency response organisations must co-ordinate more closely with each other to ensure a harmonised response to fire risk alerts and incidents.	**Forestry departments** **Disaster management authorities** **Emergency response organisations**
Sustainable funding and risk mitigation	Sustainable funding sources must be established before scaling an AI-enabled system.	**Project lead** **Development and donor partners**
	A risk mitigation plan should be developed 1) in case of limited or unreliable sources of funding, as well as 2) for maintaining the system regardless of political changes that could impact investment and priorities.	**Project Lead**

Need	Action	Actor
Capacity building	Disaster management authorities and data partners need to build capacity to transition to an AI-enabled system by learning from international deployments.	**Data partners** **International knowledge-sharing partners**
	AI for DRR should be embedded in higher education curriculums in engineering and ICT programmes.	**Institutes of higher education**
	Forestry departments need to improve capacities for digital data collection, GIS and the use of web/mobile based dashboards to understand fire risk and detection.	**Forestry departments**
	Forestry training institutes should embed digital data collection, GIS training and non-technical training on the use of AI in DRR in curriculums.	**Forestry training institutes and departments**
	AI experts should be funded to develop specific technical know-how on AI for DRR.	**Development partners** **Government** **Institutes of higher education**
Addressing key infrastructure gaps	A rapid assessment of gaps in fundamental infrastructure needed for the system, including uninterrupted power, reliable and low latency connectivity, and data storage and compute power, should be undertaken.	**Project lead**
	Key gaps in enabling infrastructure, including consistent power and connectivity, and relevant IT infrastructure such as hardware and software elements needed for AI, should be addressed.	**Project lead** **Energy providers** **Mobile operators** **Technology companies** **Software providers/ developers**
Community engagement	Forestry departments, community-based NGOs and community leaders should remain in dialogue to understand, accept and support an AI-enabled forest fire management system.	**Forestry departments** **Community-based organisations** **Community leaders**

01.
Introduction

The world is experiencing an increasing number of natural disasters. Rising global temperatures due to climate change are worsening droughts, storms, wildfires and flash floods, causing severe impacts on communities and wildlife.

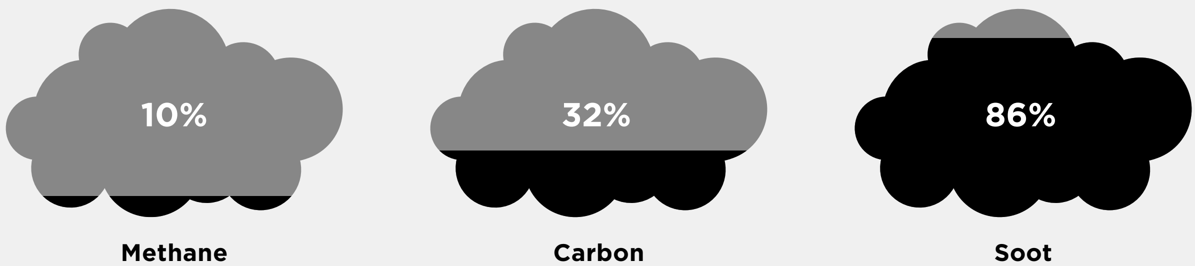
To galvanise states and the global community to minimise the devastating impacts of such natural disasters, in 2015, the United Nations General Assembly endorsed the Sendai Framework for Disaster Risk Reduction to further "the substantial reduction of disaster risk and losses in lives, livelihoods and health and the economic, physical, social, cultural and environmental assets of persons, businesses, communities and countries."[8] The framework, which guides DRR interventions internationally, identified four priorities: understanding disaster risk; strengthening disaster risk governance to manage risk; investing in DRR; and enhancing disaster preparedness and response.[9] DRR is also a key contributor to the United Nations Sustainable Development Goals (SDGs), such as the reduction of poverty and hunger, the building of sustainable cities and communities and climate action to reduce the impact of extreme weather on populations.

Recognising the worsening impacts of climate change on multiple natural disasters, and the disproportionate impact of these disasters on already vulnerable communities, in 2022, the UN Secretary General announced the Early Warnings for All (EW4All) initiative, calling for global action to protect everyone with an early warning system (EWS) by the year 2027.[10] The initiative advocates for pooling global investment to develop multi-hazard warning systems and regulatory frameworks to direct emergency response, particularly in more vulnerable and under-resourced countries where such hazards lead to exponentially more loss and deprivation.[11]

Forest fires are an increasingly worrying natural hazard. While more common in regions of the world such as North America and Australia, and in Mediterranean countries such as Italy, Greece, Spain and Portugal, forest fires can occur anywhere and have devastating consequences for human settlements and wildlife. Wildfires are virtually uncontrollable once they reach a certain size and intensity. With the hotter and drier conditions induced by climate change, the frequency and intensity of forest fires are escalating, creating a cycle of increasingly drier and hotter conditions that result in even more fires and further increase risks to lives and livelihoods.[12]

Figure 1

The contribution of forest fires to global methane, carbon and soot emissions



Source: World Wildlife Fund (WWF)

8 UN Disaster Risk Reduction (UNDRR). Implementing the Sendai Framework website.

9 The Sendai Framework further highlights seven targets and 38 indicators to measure progress on disaster risk reduction. See UNDDR: Sendai Framework at a Glance.

10 United Nations Climate Action. Early Warnings for All website. *The GSMA plays an active and ambitious role in EW4ALL, engaging with mobile network operators (MNOs) to actively engage at the national level. See: World Meteorological Organisation (WMO).* (26 May 2023). GSMA Early Warning Systems Contribution.

11 The EW4All initiative has four pillars: 1) Disaster risk knowledge and management; 2) Detection, observation, monitoring, analysis and forecasting; 3) Warning dissemination and communication; and 4) Preparedness and response capabilities. *A partnership of the WMO and UNDRR* with support from the ITU, the International Federation of Red Cross and Red Crescent Societies (IFRC) and other partners, the initiative recognises the power of increasing internet connectivity and smartphone penetration in disrupting traditional EWS, and the notable positive impact of these warnings on the reduction in loss of lives. See UN website: Early Warnings for All.

12 See the United States Geological Survey (USGS) website for a list of resources on the relationship between climate change and natural disasters.

With forests increasingly under threat, global commitments have been made to protect them. Forests play a key role in absorbing carbon and controlling GHG emissions, helping to mitigate the impacts of climate change. In 2010, the UN Framework Convention on Climate Change (UNFCCC) developed the REDD+ framework to help countries reduce emissions through better forest management techniques and provided technical and financial support.[13] More recently, the protection and conservation of forests featured heavily in the 26th meeting of the UN Conference of the Parties on Climate Change (COP26) in 2021, COP27 in 2022 and COP28 in 2023. At COP26, the Glasgow Leaders' Declaration on Forests and Land Use, a pledge by 100 countries to stop deforestation and land degradation,[14] was announced. At COP27, the European Union and 26 other countries committed to scaling actions to reverse forest loss by 2030 under the Forest and Climate Leaders' Partnership (FCLP) and commitments to forest protection and conservation were further extended at COP28. Controlling forest fires to protect forest cover and wildlife, and limit land degradation, are key to these efforts.

Figure 2

Forested areas of Pakistan

Source: Global Forest Watch: Highest resolution imagery 1-3 years old (global)

13 The REDD+ framework calls for states to have 1) a national strategy; 2) establish a forest emission level; 3) a clear monitoring system for reporting on REDD+ activities; and 4) a reporting mechanism for how REDD+ is addressing social and environmental protection.

14 UK Government. (2022). World Leaders Summit on "Action on Forests and Land Use".

Globally, Pakistan is one of the most vulnerable countries to natural hazards caused by climate change. The country ranked 8th in the world in the Global Climate Risk Index in 2021,[15] and 23rd out of 191 countries in the INFORM Risk Index, a collaboration between the Inter-Agency Standing Committee Reference Group on Risk, Early Warning and Preparedness and the European Commission.[16] While vulnerability to floods, earthquakes and droughts is higher, forest fires are a growing concern, and forest degradation is worsening the intensity and impact of other natural disasters such as floods, due to less absorbent soils.

According to Global Forest Watch, forest fires are the biggest driver of tree cover loss in Pakistan's forests.[17] In 2022, a severe and prolonged heatwave between April and July, considered the most high-risk time for fires, led to a reported 51 fires in the Swat District of the Khyber Pakhtunkhwa (KP) province alone, up from 15 to 20 fires the year before. The province of Balochistan also experienced the Sherani forest fires, which raged for 13 days and wiped out the local economy, which was dependent on harvests from pine nut trees. An estimated 900,000 trees burnt, with an approximate loss of PKR 4 billion (USD 18.6 million) a year for many years, given that the trees take between 25 and 40 years to bear fruit sufficient for commercial harvest.[18]

With the growing risk of forest fires to the environment and communities of Pakistan,[19] there is a need to improve existing fire management systems that rely on traditional and manual processes to prevent and combat fires. In 2022, more than 10% of the country was submerged in floods in which 1,700 people lost their lives, 2 million people were left homeless and economic losses totalled USD 30 billion. Heavy rainfall, extreme heat and melting glaciers, as well as deforestation that reduced the ability of the soil to absorb water, all worsened the impact. The prevention of forest fires and protection of forests will be key to reducing Pakistan's vulnerability to other natural disasters, too.

In the past decade, rapid technological developments have made AI an increasingly effective tool for predicting, preventing and mitigating the impact of forest fires, as well as other natural disasters such as floods. AI is already playing an important role in forest fire management in global fire hotspots such as Australia, the United States, Canada, Türkiye, Spain and Portugal. In low- and middle-income countries (LMICs), AI is also being used increasingly for multi-hazard EWS and, more specifically, for forest fire prediction and management. The EW4All and FCLP initiatives recognise the key role that AI can play in DRR and response.

This report highlights the role that AI can play, and is already playing, in reducing forest fires globally, and assesses how a sustainable, multi-stakeholder AI-based solution can be deployed for forest fire management in Pakistan. While the report focusses on Pakistan, learnings can be applied to forest fire management in other LMICs more broadly.

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15 German Watch. (2021). Global Climate Risk Index 2021.

16 The INFORM Risk Index is a multi-stakeholder collaboration that ranks countries on three dimensions: hazards and exposure, vulnerability and coping capacity. See the INFORM website.

17 Global Forest Watch dashboard for Pakistan.

18 Saeed Khan, R. (19 September 2022). "Long-term impacts of 'terrible' fire season in Pakistan's mountains". PreventionWeb.

19 According to Global Forest Watch, there were 1,043 Visible Infrared Imaging Radiometer Suite (VIIRS), forest fire alerts across Pakistan from 8–15 January 2024, with 2.4% considered high-confidence alerts. In 2023, there were 1,084 high-confidence VIIRS forest fire alerts. The VIIRS instrument collects visible and infrared images and global observations of the land, atmosphere, cryosphere and oceans. It is currently deployed on the SUOMI NPP and NOAA-20 satellite missions. See NASA's Earthdata website.

02. Research objectives and methodology

Research objectives

The aim of this report is to present opportunities for harnessing AI-enabled solutions for better wildfire risk management, taking as an example forests in Pakistan's KP province and the Islamabad Capital Territory (ICT), both areas that are highly vulnerable to forest fires.

Specifically, this research aims to:

- Provide an overview of existing forest fire management practices globally.
- Identify the role AI is playing in improving traditional wildfire management, and the institutional, technical and financial capacities required for such a solution.
- Present AI-enabled solutions that are deployed internationally at scale to minimise the risk of, and mitigate the damage caused by, forest fires.
- Evaluate Pakistan's preparedness to implement an AI-enabled system to mitigate the risk of forest fires, taking a broad approach that can be replicated in other contexts.
- Present steps that key stakeholders can take to implement a comprehensive, national AI-enabled wildfire management system in Pakistan and in other LMICs facing similar challenges.

Methodology

The methodologies used for this research are outlined in Table 1.

Table 1:
Research methodologies

Data source	Objective
Desk-based research	Develop an understanding of the current state of AI-based solutions for wildfire management globally. Inform a landscape review of existing forest fire mitigation initiatives in Pakistan.
Focus group discussions with: — 40 attendees, including district forest officers (DFOs) responsible for overseeing forest management, and community leaders in forest-dwelling communities in Pakistan. — 15 public, private and third-sector actors, including those working in key government ministries, disaster management, forest management, emerging technologies, academia, non-governmental organisations (NGOs) and the telecoms sector.*	Understand the causes of forest fires in Pakistan and the role of forest-dwelling communities in using and participating in the protection of forests. Understand the strengths and limitations of current forest fire management procedures and practices in Pakistan. Sensitise an AI-enabled approach to natural disaster management in Pakistan and key enablers. Explore the capacity and resources available to shift to a more digitised process. Identify areas of collaboration in building an AI-enabled forest fire management system.
Semi-structured interviews with key government ministries, disaster management authorities, public and private emerging technology and data providers, and development partners and NGOs involved in forest conservation in Pakistan, as well as international organisations developing AI-enabled solutions to mitigate forest fires.**	Map existing initiatives and organisations involved in forest fire management in the country and understand their institutional capacities and constraints. Identify pain points in forest fire management. Understand existing AI-enabled forest fire management initiatives in other contexts that can help inform Pakistan's strategy. Identify recommendations and best practices for the implementation of AI-based solutions and the enabling framework (e.g. institutional capacities and stakeholder coordination).

*A full list of focus group attendees can be found in the Acknowledgements.
**A full list of organisations interviewed can be found in the Acknowledgements.

The findings of this report can be used by Pakistan's disaster management authorities, as well as development partners, academia and public and private sector data and technology partners to collaborate to institute a phased, incremental approach to building an AI-enabled forest fire management system in Pakistan. They can also serve as a guide for other countries conducting a readiness assessment and implementing a similar system.

03.
Key determinants and traditional management of forest fires

Determinants of forest fire outbreaks and intensity

There are three key determinants of a forest fire outbreak: an ignition source, the presence of combustible fuel and exposure to air. Ignition sources may be natural (e.g. lightning) or anthropogenic (caused by human behaviour, such as a lit cigarette or controlled agricultural burns). In many cases, including in Pakistan, fires are caused primarily by human activity.

Dry vegetation tends to serve as combustible fuel and heavily impacts fire intensity. Fuel features, such as the type of vegetation, the moisture content of the vegetation, the amount of dry vegetation build-up on the forest floor (fuel load) and the shape of vegetation, all affect the intensity of a fire.

Weather also has notable impacts on fire intensity and spread. Wind, for example, is a necessary condition for spread, and wind speed and direction also influence intensity. Similarly, the amount of humidity and precipitation and the temperature affect both the spread and intensity of a fire.

Topography, including features like elevation and slopes, affect the spread of a fire by influencing how heat transfers between spaces.

The key determinants that fuel a forest fire, therefore, can be summed up as:

— **Fuel features:** type, moisture, load and shape

— **Weather features:** temperature, wind, precipitation and humidity

— **Topography:** elevation, slope, aspect and position of fire (at the top or base of a slope)

These variables have both temporal and spatial components. Fuel features and weather conditions vary by time of year and forest region, making the risk and intensity of fire outbreaks variable by season and location.

In addition, where forest fires are caused primarily by human activity, social data such as the location of human settlements and movement patterns of people in and around forests and the location of mobility infrastructure such as roads and trails, are valuable additional parameters for predicting the outbreak and impact of fires.

Traditional management of forest fires

There are established standard operating procedures (SOPs) for combatting forest fires in most countries prone to outbreaks. They vary in effectiveness and fall into four broad categories: prediction, prevention, detection and management, and response and recovery.

Figure 3

Traditional fire management activities

Prediction	Prevention	Detection and management	Response and recovery
Using historical data on fire outbreaks to create hazard maps, taking into account both temporal and spatial components.	Sensitising and raising the awareness of forest-dwelling communities on how to prevent fires and their impact.	Surveillance through ground patrols.	Fire-fighting using standard tools.
	Legal enforcement of rules established to prevent forest fires caused by human activity.	Surveillance through fixed infrastructure such as fire towers and/or equipment such as cameras.	Post-fire damage assessment and plantation.
	Clearing fuel build-up from the forest floor.	Creating and maintaining fire break lines to prevent small fires from crossing over and spreading to other areas of the forest.	
	Deploying additional resources for patrols in identified high-risk areas and seasons.	Building road infrastructure to access forest regions to put out fires.	

Source: GSMA Mobile for Development

The effectiveness of these activities depends on available funding and well-trained and well-equipped human resources.

There are numerous gaps and challenges in fire management systems that are compounded in low-resource settings. Risk assessments are generally not comprehensive given the number of parameters involved in determining the ignition and spread of a fire, leaving room for error. The level of surveillance that can be undertaken by human patrols is also limited, which means many regions may go unsurveilled. Inefficient alert systems lead to delayed responses in situations where time is of the essence. Regeneration efforts may be *ad hoc* and not consider topography and weather conditions, for example, which can limit their success.

AI can play a key role in overcoming many of these limitations, significantly reducing the risk and improving the management of forest fire outbreaks. The following section presents the opportunities that AI offers in forest fire management.

Key Insights

Despite well-established practices and protocols within forest management agencies worldwide, human capacity for accurate prediction, early detection and effective management of forest fires is limited. AI provides an opportunity for leveraging data to efficiently assess fire risks and promptly detect outbreaks, significantly curbing fire occurrences and mitigating their spread. Consequently, integrating AI into forest fire management can markedly improve overall effectiveness in combating wildfires and improving DRR more widely.

04.
The role of AI in forest fire management

AI for forest fires: a framework

Forest fire management can be improved at various stages via AI, from predicting fire risks and early fire detection to managing active fires and facilitating response and recovery efforts.

AI is a process by which computers or other machines are trained via an algorithm, or set of instructions, to detect patterns in large datasets for classification and prediction purposes.[20]

Transitioning from conventional to AI-driven forest fire management depends on a crucial pillar: data. There needs to be sufficient useable data for AI model training. For the data to be useable, it needs to be complete, accurate and in a format that can be processed by an AI algorithm. Key sources of this data include historical records of forest fires, data generated by sensors on satellites, Internet of Things (IoT) devices and cameras. There are substantial costs associated with the development of such a system (discussed in section 6), requiring sustainable funding along with adequate human resources and technical proficiency.

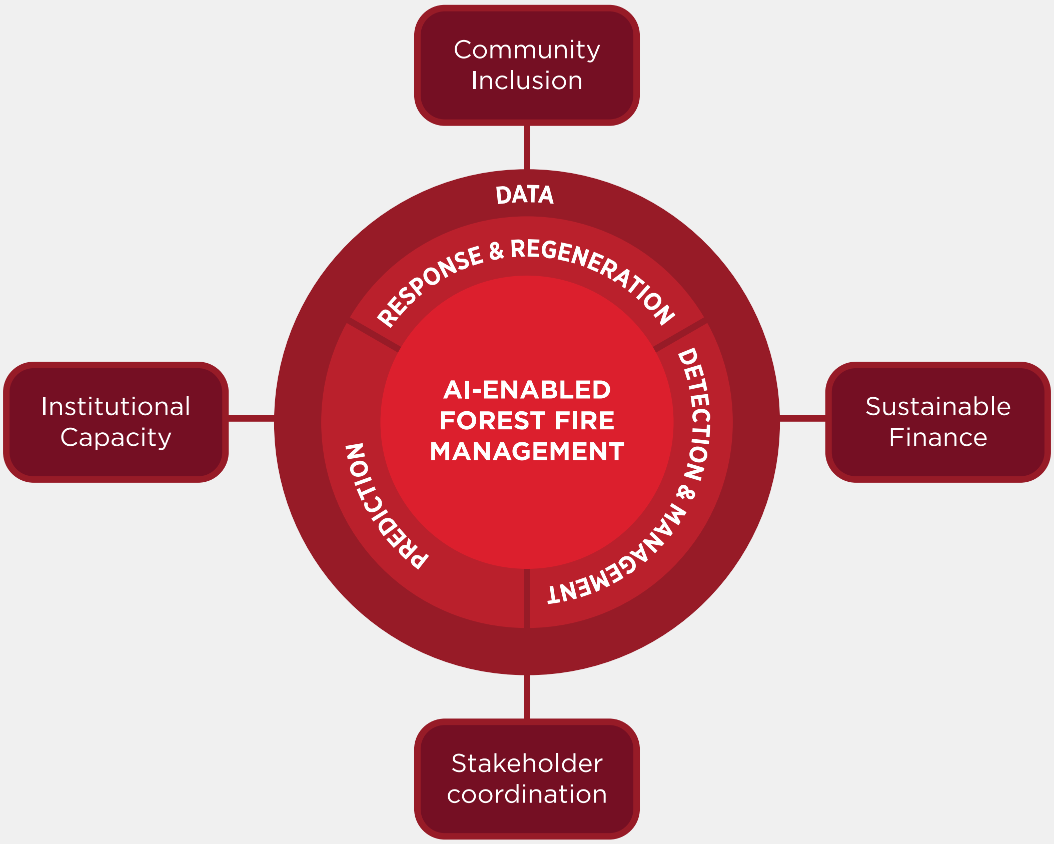
The effective development of an AI-enabled forest fire management system also requires collaborative efforts among diverse stakeholders, from public sector disaster management authorities and forestry departments to data and technology partners. This not only ensures that a highly reliable system is constructed, but also that it is used efficiently for early warnings and prompt response to prevent fire spread. Additionally, engagement with forest-dwelling communities is integral to inclusive and effective fire management.

Figure 4 provides a framework for the enablers of an AI-enabled forest fire management system.

20 GSMA. (2023). "The synergy of big data and AI". AI for Impact Toolkit.

Figure 4

A framework for deploying an AI-enabled forest fire management system



Source: GSMA Mobile for Development

AI models for forest fire management

AI models for forest fire management include machine learning (ML) and deep learning (DL) models.

In ML models, human intervention is needed to identify certain parameters (i.e. conditions that influence the risk of or indicate a fire, such as temperature, level of humidity in the soil or elevation of the land) and input these into an algorithm to train an AI model to predict an outcome or classify an event. The classifier is the specific algorithm used for this task – a model for processing data that, when built effectively, can classify an object or event or predict a binary outcome to a high degree of accuracy.

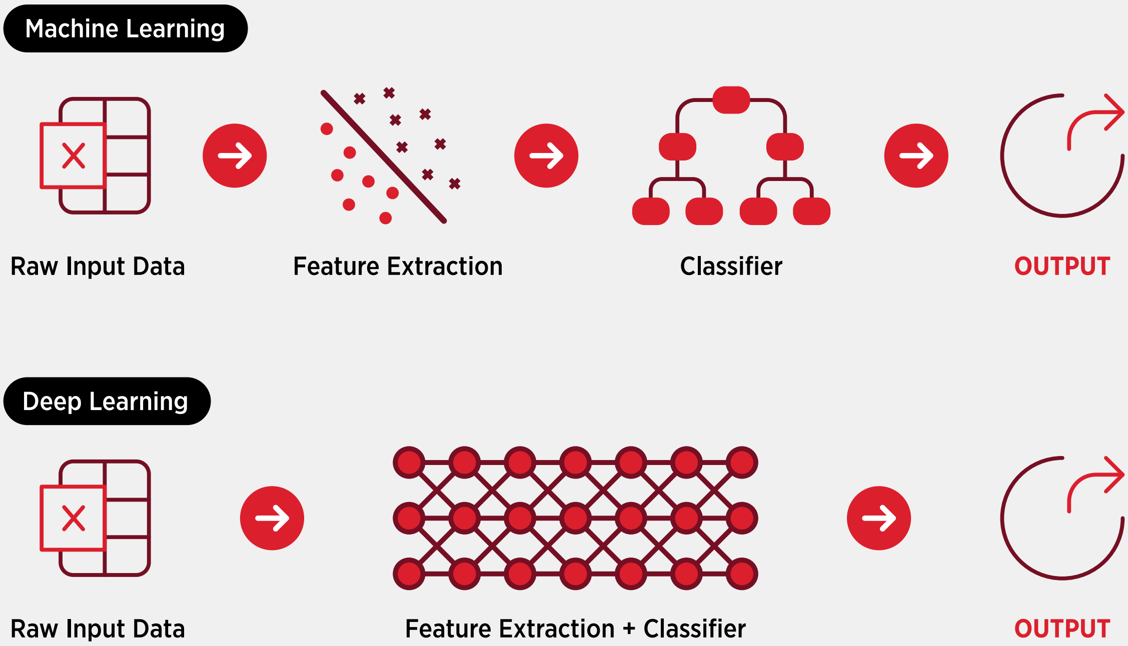
In ML models, available data is split into training data – the initial dataset used to train the ML model to predict or classify – and testing data, whereby new data that the model has not seen during the training phase is used to evaluate how accurately the model is working.

DL models, on the other hand, are designed to independently extract relevant features from raw data to make predictions or classifications without the need for human intervention (Figure 5).

Computer vision is an AI process whereby computers are trained to understand and interpret visual images. DL models can use large image datasets to detect patterns to classify or identify an object or event, and then react accordingly. The most common types of imagery and their data sources for AI-enabled forest fire management are captured in Table 2.

Figure 5

Machine Learning (ML) and Deep Learning (DL) models for forest fire management



Source: Nature Clicks Institute

Table 2:

Types of imagery used to train DL models for forest fire management

Type/source of imagery	Description
Satellite imagery	Used to capture images of Earth from space, these images help to monitor large forested areas and provide an overview of vegetation health, land cover and potential fire-prone regions.
Aerial imagery	Captured via aeroplanes or drones, these images can monitor specific areas of forests to provide detailed, high-resolution images.
Infrared imagery	An infrared camera is used to detect areas of unusually high heat that may indicate fire.
Thermal imagery	Captured via thermal cameras or sensors, thermal imagery can detect heat in low-visibility settings, such as at night or in fog.
Historical imagery	Captures the same physical spot over time to enable an assessment of changes to land and vegetation.
Visual imagery (of smoke plumes)	Images of smoke plumes can help in understanding the direction and spread of fire.

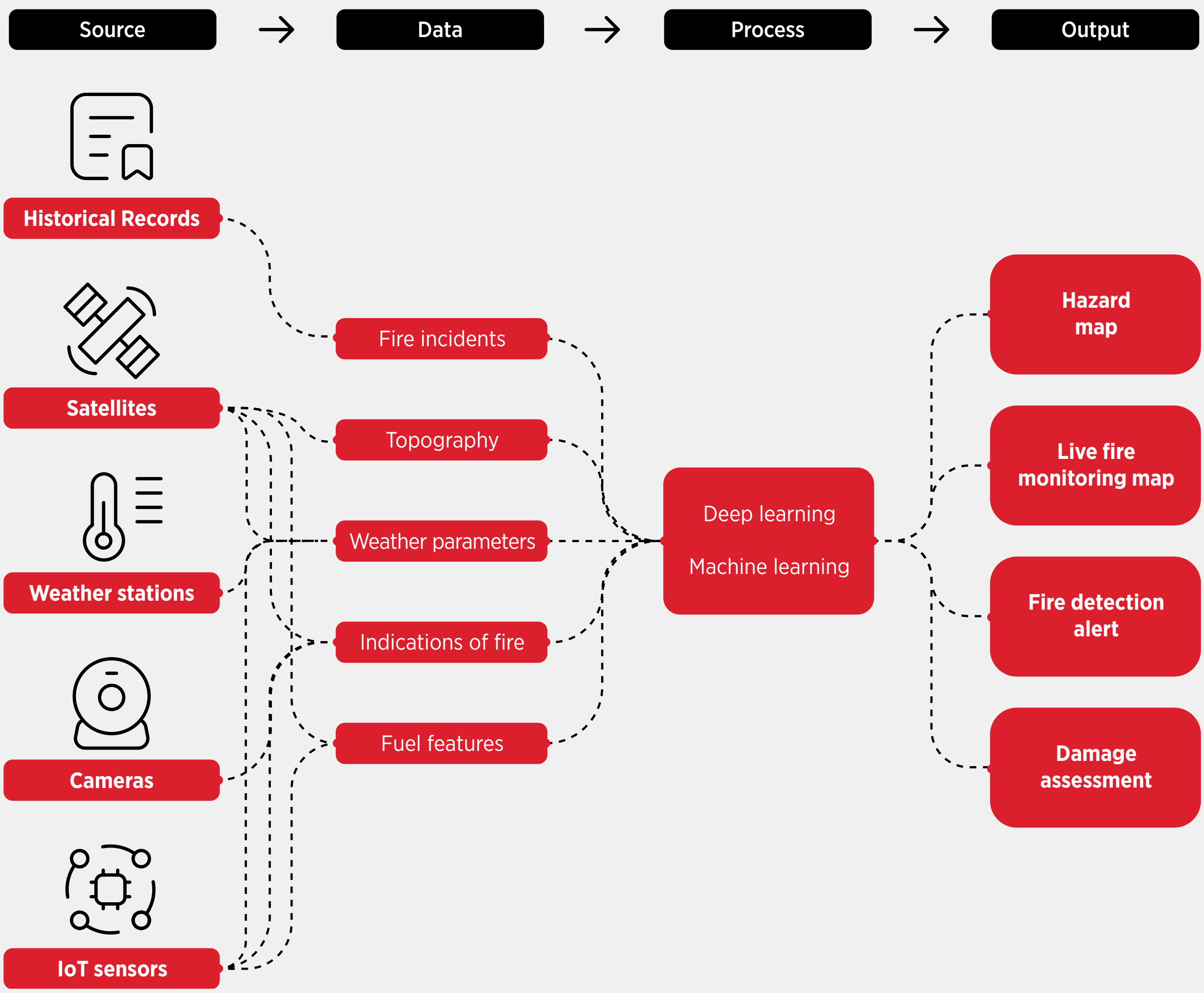
ML and DL can be used at each stage of a forest fire outbreak. Parameters such as historical data on fire events, weather, topography and fuel features in forests can be fed into ML models to predict the risk of a fire outbreak. Indicators such as images of smoke plumes, the release of gases (e.g. carbon dioxide and carbon monoxide) and changes in temperature captured via cameras and sensors in forests or mounted on drones or satellites, can signal the occurrence of a fire before it spreads. Real-time monitoring using this data can prompt immediate notifications to disaster management authorities and forestry teams and cut down response time, which is crucial to prevent fire spread.

This data also enables disaster management authorities and forest departments to monitor the progression of a fire and predict its trajectory and speed, enabling a more strategic response. Integrating this information on an online dashboard that provides a live visual map for monitoring the fire also significantly enhances their ability to respond more effectively to a changing situation (Figure 6).

Beyond prediction, early detection and management, AI can also be used to assess fire damage, including burnt area estimates, using images of pre- and post-fire landscapes.

Figure 6

AI for integrated fire management: prediction, detection, management and response



Source: GSMA Mobile for Development

Data for AI-enabled forest fire management

As noted earlier, the training of AI models depends on the availability of large amounts of useable data. An invaluable source of existing data for fire risk prediction is historical records of forest fires and the conditions in which these fires ignited. These records can be a key resource for training AI models to learn from past spatial and temporal data to predict forest fires in a particular region in the future.

Countries where detailed records of forest fires have been maintained have an advantage over those with spotty and limited records of forest fires informing their AI algorithms.

Where such records are not available or not useable, spatial and temporal data based on remotely sensed images captured by satellites have been a key resource in AI-enabled forest fire management.[21]

Satellite data

Some key satellites providing remote-sensing data for forest fire risk prediction and detection include the NOAA, Aqua and Terra satellites launched by NASA and the National Oceanic and Atmospheric Administration (NOAA), the Landsat satellite launched by NASA and the US Geological Survey,[22] as well as the Sentinel satellites launched by the European Space Agency (ESA).[23] These satellites provide different types of information on the Earth's surface, enabled by sensors such as the Moderate Resolution Imaging Spectroradiometer (MODIS)[24] onboard the Terra satellite, and the Visible Infrared Imaging Radiometer Suite (VIIRS)[25] on the NASA/NOAA Suomi NPP and the NOAA-20 satellites, which builds on the data provided by MODIS. Both are key sources of remotely sensed data for forest fire prediction and detection. Data from the Landsat series of satellites is particularly effective at informing post-fire assessments of burnt areas.

Alongside the US, several other countries such as Canada, Italy, Germany and Spain, have launched their own satellites that generate relevant data for AI-enabled forest fire prediction and early detection. For example, the Canadian Forest Service (CFS) has announced plans to launch WildFireSat Canada[26] in 2029, a wildfire monitoring satellite equipped with infrared sensors, in collaboration with the Canadian Space Agency (CSA), Natural Resources Canada and Environment and Climate Change Canada. The initiative aims to enhance the monitoring of fire, smoke and carbon emissions.

A geographic information system (GIS) software tool, which enables the mapping and analysis of geospatial data (i.e. what things are and where they are located geographically on a digitised map), is generally used for analysis. Different types of geospatial data are layered onto the digital map, and risk predictions or early detection of a forest fire using remotely sensed data can be mapped onto the GIS layers to develop a comprehensive visual hazard map. GIS data on human settlements, infrastructure such as roads and trails and natural features such as rivers and streams, can help improve the model.

While satellite images are cost-effective to access, they lack the necessary resolution and frequency for early detection, particularly at night and during cloudy conditions, and may not detect small fires. Recently, national space agencies and private companies have launched forest fire monitoring satellites to address these limitations. For instance, the German company OroraTech[27] has launched a dedicated forest fire monitoring satellite, FOREST 1. This satellite processes images using AI, sending alerts to relevant authorities within three minutes rather than transmitting high volumes of raw data. OroraTech augments their DL model with image data from 20 additional satellites. The company was engaged by ARAUCO, a large forestry company in Chile, to assist in early fire detection following devastating forest fires in February 2023.[28]

There are a growing number of commercial initiatives. For example, optical data is being provided by satellites such as the Pléiades Neo, Vision-1, the WorldView series, GEOSAT and SPOT-6.[29]

21 Remote sensing is the process of detecting and monitoring the physical characteristics of an area from a distance by measuring its reflected and emitted radiation. Source: NASA Earthdata: "What is Remote Sensing?".
22 See Landsat Science website.
23 See the European Space Agency website: The Sentinel missions.
24 See: About MODIS on the NASA website.
25 See: About VIIRS on the NASA Earthdata website.
26 See the Canadian Space Agency website for more information on WildFireSAT.
27 See the OroraTech website: Wildfire Detection and Monitoring from Space.
28 OroraTech. (14 March 2023). "OroraTech & Arauco: Battling Devastating Fires in Chile".
29 ESA. (17 August 2023). "Commercial and international data for fire monitoring".

Accessing satellite data

Remotely sensed data on wildfires is accessed in a variety of ways. For example, NASA's FIRMS uses MODIS and VIIRS data to provide updates on active fires throughout the world, including the approximate location of a detected hotspot. Imagery is available within four to five hours of a fire outbreak. NASA also offers the Wildfires Data Pathfinder,[30] which provides open-source global data on parameters for pre-fire data, active fire data and post-fire data analysis.

The ESA's Copernicus Climate Data Store[31] is another valuable resource that combines data from the Sentinel satellites with other sources of climate data, and is a large, freely accessible database of Earth observations. The ESA also combines data from 45 different satellite sources, both public and commercial, under its Third Party Missions (TPM) programme and provides it for free to developers and researchers.

A significant challenge with using image data to detect small fires early, especially at a high enough resolution, is the considerable expense and computing requirements for transferring, storing and processing images continuously. AI applications operating directly on the devices capturing these images (edge computing), such as those offered by OroraTech, can mitigate the substantial costs involved in central data storage and processing on the cloud, but may introduce higher upfront costs.

30 See NASA Earthdata website: Wildfires Data Pathfinder.
31 See Copernicus Climate Data Store website.

Other sources of data

Cameras

Optical, thermal and infrared imagery that can indicate a fire via visual cues and detect heat hotspots can also be captured via cameras tailored to this purpose. Cameras can provide much higher resolution images than satellites and in real time, giving them an edge over satellite data.

Optical cameras can detect smoke plumes, enabling fires to be detected within minutes, and can also provide a live feed of a spreading fire to enable real-time observation of spread and intensity. Pan-Tilt-Zoom (PTZ) cameras are a particularly effective tool for monitoring a forest range from a high altitude.

In other cases, cameras that have been deployed for other surveillance purposes can also be used for fire surveillance. For example, Hong Kong-based company Robotic Cats[32] relies heavily on visual data from surveillance cameras to detect forest fires. The company has developed software that turns images of fires from surveillance cameras and even Android phones into useable images to train an AI model to identify fires and issue alerts. The company encourages public participation through an app that allows users to share images of fires and contribute to an increasingly large database for improved model training. Robotics Cats' solutions are currently deployed in multiple markets, including the US, Australia and Colombia.

However, to train AI models to accurately detect fire in images requires large training datasets that contain images of forest fires. These are challenging to obtain as natural disasters, by their very nature, do not occur frequently and are not regularly captured in images. Training AI models to use image data, therefore, has been a persistent challenge that affects the accuracy of prediction.

Thermal cameras capture temperature changes and can be used in isolation or in combination with optical cameras for early detection of forest fires or to highlight very hot regions with a higher fire risk.[33] Unlike optimal cameras, thermal cameras can work in low-light conditions but require much higher maintenance and are much more resource intensive. They are also less suited to situations where access to power is a challenge.[34] Like satellite data, optical and thermal imagery from cameras can be processed using AI on the cloud (once transmitted) or on AI-enabled devices themselves to detect fires and predict fire risk by identifying areas of high heat.

IoT sensors

IoT sensors can be installed in forests to generate data on and monitor parameters such as humidity, wind speed, temperature, soil moisture, solar radiation and the presence of gases such as carbon monoxide, carbon dioxide, nitrogen oxide and hydrogen. This enables a fire to be detected before it has even ignited. Data generated from sensors can be used to inform AI models for risk prediction.

Unlike cameras, IoT sensors do not rely on visual cues and are therefore not affected by adverse weather conditions and/or low-light conditions. They are a cost-effective and low-maintenance solution to data gathering for AI models, as well as monitoring, although extensive networks of sensors may be needed for monitoring to be effective.

There are examples of exclusively IoT-enabled AI for forest fire management systems. German company Dryad Networks[35] has developed a low-cost, solar-powered sensor that operates like a "nose" to detect smoke. The network of sensors can issue alerts as soon as smoke is detected, providing early warnings. The data is processed in the cloud using AI, and the solution has been piloted at sites in Spain, Italy, the UK and Lebanon.

32 See Robotics Cats website.
33 InfiRay. (n.d.). "3 Benefits of Thermal Imaging in Wildfire Detection and Management".
34 See Industry Search for more information.
35 Ibid.

Box 1:

Drones for remote oversight

Drones equipped with sensors and cameras can be a useful tool for accessing remote and hazardous areas where human intervention is risky, such as into a blazing fire, to provide situational awareness. Whether self-flying or remote-controlled, they need to be operated by trained personnel and require a “hub” from which they can be recharged and controlled. Drones are resource-heavy and require regular maintenance.

Examples of AI-equipped drones deployed in post-event response to forest fires include a recent project in the United States by University of California (UC) Davis launched in March 2023.[36] Researchers are using drone-captured images of the university’s natural reserve system, which consists of 41 reserves, to identify the impact of a fire, mitigation measures and post-fire recovery. The project uses images collected several years ago before four fire events. After the fire outbreaks, drones captured post-fire images of the burnt reserves. Researchers are currently conducting additional drone flyovers to capture recent images of healthy versus burnt areas to assess the impact of regeneration efforts.[37]

The information technology infrastructure and hardware company Huawei has recently developed a drone that can detect smoke and fire, enabling early response. The drone is AI-enabled to process images in real time and supported by a 5G network.[38] The use case is being trialled in Cyprus under Huawei’s Smart & Green Village programme.

Weather stations

Modern weather stations have become a key resource for natural disaster risk prediction and management. Weather stations can generate data on atmospheric conditions such as wind speed and direction, humidity, air temperature and precipitation to inform AI models for fire risk prediction and fire spread. Advanced weather stations can also use remote sensing and radar technology to collect increasing amounts of data on meteorological conditions. This data is transmitted in real time to either meteorological departments that then transmit it to disaster management authorities and first responders, or it can be shared with them directly.

Weather stations can vary vastly in their capabilities and the types and amounts of data they generate, and can be resource-heavy, requiring strategic deployment.

While weather station data is transforming forest fire prediction, it is critical that the data is accurate, as small errors in assessment can have catastrophic results. The accuracy of weather data is especially imperative, as weather parameters play a significant role in the occurrence and spread of fires. For example, an error in the assessment of wind speed by 5 mph can, in certain situations, result in the rate of spread of a fire being underestimated by half.[39]

In addition, all these data sources, including cameras, drones, sensors and weather stations, depend on good-quality connectivity. The more data they transmit, the greater the data transmission challenges and the higher the associated costs, especially in forests, which can be remote. In recent years, LoRaWAN (long-range, wide-area networks), a type of data transmission network that can transmit small amounts of data over large distances without needing a SIM or Wi-Fi connectivity, are becoming increasingly popular for connecting IoT sensors, which transmit small amounts of data where connectivity is a challenge. The useability of other devices depends on the availability of good-quality connectivity.

36 Wong, K. (29 March 2023). Using AI to Analyze Wildfire Impacts: A Toolkit to Assess Ecosystem Resilience to Wildfire. UC Davis.
37 Ibid.
38 Huawei. (24 October 2023). “Huawei unveils smart fire detection solution using 5G, AI and drones, under the “Smart & Green Village” program in Cyprus”.
39 AEM. (2022). The Importance of a Dedicated Wildfire Weather Network.

Box 2:

Addressing false positives

False positives, or when an AI model mistakenly predicts the high risk or occurrence of a fire, are a frequent challenge in AI-based fire detection methods. Adverse weather conditions, restricted vision, limited training data and the presence of controlled fires can all lead to AI-enabled cameras and sensors issuing fire alerts erroneously. False alerts can put a huge strain on resources and be a deterrent to using AI for forest fire management. The following methods can be used to overcome some of these challenges:

— Combining resources: Using multiple technologies in combination to obtain more and better data (e.g. using IoT ground sensors alongside optical cameras).

— Offline training: The accuracy of AI algorithms improves over time as more data is added. Training the algorithm offline (e.g. using historical data and data from simulations of a scenario where no data is available) can speed up this process. Data from simulations can fill a large data gap when it comes to natural hazards, which are infrequent events and therefore not conducive to big data.

Due to the challenge of false positives, an AI-enabled forest fire management system should not be intended to replace human monitoring of forest fires, but rather used to enhance and support human monitoring. Therefore, if the possibility of false positives is built into the fire response strategy, resources can be allocated efficiently. This could include hiring staff to run checks on the alerts before passing them on to the relevant authorities and having a clear plan to feed additional data into the algorithm.

Factors that ultimately determine the right mix of data sources and technology deployments for an AI-enabled forest fire management system include: the number and size of high-risk areas; the availability of financial and human resources to deploy and maintain devices; and the data requirements. The deployment of multiple technologies is likely to improve both risk prediction and detection, as they enable an optimal amount of data sources and parameters to train AI models and reduce or eliminate the occurrence of false positives.

Box 3:

Forest fire management in Australia: planning an optimised AI-enabled system

Australia faces recurrent and extensive damage from bushfires, prompting the development of innovative AI-driven fire monitoring initiatives.[40] The Australian National University (ANU)-Optus Bushfire Research Centre of Excellence[41] is developing and testing an integrated fire management system that will deploy a range of AI-enabled technologies for early detection. Technologies include a network of advanced electronic sensors to predict lightning ignition, ground sensors to monitor environmental conditions and emissions, cameras placed on fire towers to detect smoke in images and drones equipped with thermal cameras for night vision, combined with data from satellites to detect fire hotspots.

The electric sensors will be AI-enabled to triangulate lightning strikes during a thunderstorm with highly accurate prediction. This information from the sensors will be combined with environmental data like temperature and fuel load to identify high-fire risk lightning strikes using ML.

The IoT sensors on the ground will detect smoke and are also "smart", that is, able to learn to improve detection. The cameras will detect smoke using AI and identify the specific source and location of smoke rather than a general area. However, for the model to do this accurately, local datasets of fire smoke images are needed and these are currently limited. The drones will be equipped with thermal cameras for night vision, able to fly in conditions immediately following a thunderstorm to detect fires and AI-enabled for detection.

Such a comprehensive solution aims to overcome the current challenges of satellite data-based detection in the country, as small fires in Australia tend to go undetected due to either low spatial or temporal resolution of satellite images.

As noted earlier, for forest fire forecasting to be accurate, it is essential to know fuel moisture content. Current ML models capture current fuel moisture content based on a number of parameters, but do not predict fuel data at a later stage. Researchers at ANU have attempted to predict fuel features using DL to a high degree of accuracy, further improving risk prediction.

40 The Australian Space Agency implements satellite data-based AI forest fire management systems. Additionally, the company Pano has deployed AI-enabled cameras strategically for early forest fire detection within Australia's Green Triangle Belt.

41 ANU. (1 October 2020). The ANU-Optus Bushfire Research Centre of Excellence.

Box 4:

The increasing role of AI in forest management

AI is being increasingly used in forest management for applications beyond forest fire management, such as for wildlife protection and to inform afforestation initiatives.

In 2020, for example, Rainforest Connection (RFCx),[42] a not-for-profit organisation tackling illegal deforestation, partnered with Huawei, a Chinese ICT infrastructure and hardware company, under the TECH4ALL initiative[43], to detect illegal logging activity in the Palawan rainforest in the Phillipines.[44] RCCx trialled an AI-enabled open acoustic monitoring system, a sound monitoring device that can issue alerts if it "hears" a particular sound. Upcycled smartphones provided by Huawei were embedded in the forest canopy to record auditory data. Huawei also provided its cloud platform for data collection and processing. AI was used to identify sound frequencies that indicated a chainsaw. Philippines-based mobile operator, Smart Communications,[45] facilitated wireless connectivity to enable data transfer from the smartphones to the Cloud platform. In two years of active deployment, the pilot generated more than 2,300 chainsaw alerts, enabling authorities to take action against illegal logging.

In a different approach to illegal deforestation, in 2020 WWF-Netherlands partnered with other non-profit organisations, academia and the private sector to develop Forest Foresight, a satellite data-based AI model, with the aim of preventing illegal deforestation.[46] Satellite imagery was used to scan the rainforest, and data was fed into an ML model that predicted the risk of deforestation based on the location of human settlements and human movements in the forest. The initiative was piloted in Indonesia and Gabon. It enabled forest rangers in Gabon to prevent illegal gold mining activities, saving 30 hectares of forest. It also prevented the construction of illegal roads in Kalimantan in Indonesia, protecting the forest. Forest Foresight has since been deployed in Malaysia, Surinam and Guyana.

In another example, in 2020, Bôndy, a social impact start-up delivering afforestation projects in Madagascar, partnered with Omdena, an AI developer headquartered in the US, to understand the impact of its tree plantation efforts.[47] Omdena used open satellite and meteorological data as well as data from Bondy's surveillance drones and field data, to test AI models that could accurately identify tree patches and the number of trees in a patch. The model continues to be refined so it can inform reforestation efforts.[48]

Key Insights

AI-enabled forest fire management relies upon access to extensive datasets. Principal sources of this data include remotely-sensed information gathered by satellites, as well as data derived from on-the-ground technology deployments, such as cameras, IoT devices, and weather stations. Some initiatives for forest fire management leveraging AI utilise a combination of these technologies, while others rely solely on one.

Strategic selection of data sources is important, and should align closely with the objectives of the implementation as well as the available resources, to ensure that the chosen data sources effectively support the intended goals of the forest fire management initiative while optimising resource utilisation.

42 See Rainforest Connection website.
43 See Huawei tech4all website.
44 Rainforest Connection. (September 2023). Harnessing the Power of Sound and AI to Track Global Biodiversity Framework (GBF) Targets.
45 See Smart Communications website.
46 See WWF Netherlands website: Forest Foresight.
47 Omdena. (N.D). "Tree Detection for Reforestation in Madagascar Using Satellite Imagery".
48 Omdena. (13 September 2022). "Monitoring Reforestation Success using Machine Learning".

05.
AI for forest fire management: international examples

AI-enabled systems vary by country and context and different approaches are being trialled and improved. Larger-scale and more mature AI-enabled systems can be found in well-resourced, fire-prone countries such as the US, Canada, Australia, Türkiye, Italy, Chile, Brazil and Spain. AI-enabled pilots and more limited-scale initiatives are proliferating across LMICs such as Algeria, Tanzania, Nepal, Ethiopia, India and Indonesia.

This section features examples of three different types of AI-enabled forest fire management systems.

FireAId in Türkiye

Türkiye was ravaged by forest fires in 2021, causing loss of human life and leaving 800 people injured.

In 2022, the FireAId pilot was launched to test an AI-enabled forest fire prediction system.

Figure 7

Partners and their roles in FireAId

Technical partners	Funding partner	Advisory partner	Key public sector authority
Koç Holdings	Koç Holdings	World Economic Forum; Centre for the Fourth Industrial Revolution (C4IR)	Türkiye Ministry of Agriculture and Forestry
Deloitte			

Objective

The objective of FireAId was to enable the Turkish Ministry of Agriculture and Forestry to have timely warnings of fire outbreaks to shift firefighting resources away from low-risk areas to high-risk areas as quickly as possible, while ensuring that all regions remain protected through a "chain of relocations" between areas.[49]

Process

The FireAId team first developed a fire risk map using existing datasets. It then prepared an optimal resource allocation model in case of a fire event. In the first stage of development, meteorological data was used to assess risk and historical records of forest fires were used to build a hazard risk map, with a dashboard indicating risks housed at the Ministry of Forestry and Agriculture. Vegetation and topographical data were also integrated to improve the model. Meteorological data for FireAId is collected from weather stations and updated hourly, and meteorological predictions for the coming days are also used to assess risk. Notifications of fire events are received from the Ministry and help to improve the model.

Results and outlook

The pilot, which is informed by more than 400 data parameters from 14 different datasets, had an 80% accuracy rate in predicting wildfires 24 hours before their outbreak.[50] This provides a strong case for the use of AI to enhance existing forest fire management systems and provides an example of how this can be done without deploying significant additional technologies to collect data. Building on the success of the pilot, Koç Holdings has begun the process of scaling the model for use in all regions of Türkiye.[51]

49 World Economic Forum. (2023). The Next Frontier in Fighting Wildfires: FireAId Pilot and Scaling.
50 Ibid.
51 World Economic Forum. (16 January 2023). "Successful Pilot Shows How Artificial Intelligence Can Fight Wildfires".

RISICO in Ethiopia

Ethiopia is experiencing hotter and drier conditions, increasing the risk of forest fires. In 2020, Italy-based CIMA Research Foundation conducted a project aimed at predicting the risk and mitigating the severity of forest fires.[52]

Figure 8

Partners and their roles in RISICO Ethiopia

Technical partner	Development partner	Funding partners	Key public sector authorities
CIMA Research Foundation	UN Disaster Risk Reduction Agency (UNDRR)	Italian Agency for Development Cooperation (AICS)	Ethiopian Disaster Risk Management Commission (EDRMC)
		Italian Ministry of Foreign Affairs and International Cooperation	Ethiopian Meteorological Institute (EMI)
			Ethiopian Environment, Forest and Climate Change Commission (EFCCC)

Objective

The project aimed to adapt the AI-enabled forest fire forecasting system deployed in Italy to provide risk assessments and forecasts on an open-source data information system. This system could integrate multiple sources of data for hazard risk mapping and connect multiple agencies to fire risk information. At the implementation level, the goal was to train local agencies to manage and use the system effectively to respond to forest fires.

Process

CIMA Research Foundation adapted two Italian open-source technological tools to enable Ethiopia's authorities to mitigate forest fire risks: RISICO, which is used to assess the level of risk of an already ignited fire, and myDEWETRA, an open-source dashboard that can integrate information from RISICO with global, national and regional data, and make it accessible to multiple agencies.

RISICO integrates meteorological data and weather forecasts with vegetation cover and topography data to forecast fuel moisture content and the expected rate of spread and intensity of a fire (Table 3).[53] The model delivers risk maps at the national level via myDEWETRA,[54] a real-time data integration and visualisation system for risk forecasting, monitoring and prevention that can be used for multi-hazard risk assessments. Owned by the Italian Civil Protection Department, the platform is licensed and can be used to visualise forest fire data from satellites such as MODIS, meteorological forecasts from satellite data, data from static datasets such as historical records of fire outbreaks and RISICO forecasts of fuel moisture content, wildfire rate of spread and intensity.

Forecasts generated in myDEWETRA in Ethiopia are delivered to the EFCCC via an early warnings bulletin generated three times a week, with 3-, 4- and 7-day forecasts for fire risk, and shared with relevant forestry staff on the Telegram chat app.

52 CIMA Research Foundation. (n.d.). "Disaster Risk Reduction Capacity Building in Ethiopia: development of an information management system for early warning for forest fires in Ethiopia".
53 Perello, N. et al. (2022). "RISICO, An Enhanced Forest Fire Danger Rating System: Validation on 2021 Extreme Wildfire Season in Southern Italy". *Environmental Sciences Proceedings*. 17(1):37.
54 Ibid.

Table 3:

RISICO in Ethiopia

Input sources	Data	Process	Output
Numerical weather prediction model based on the Global Forecast System[55] from data generated on the NOAA satellite.	• Vegetation cover (land use and forest maps) to inform fuel load assessment. • Topography. • Burnt area (from satellite sources) to inform fire susceptibility maps. • Position of anthropogenic infrastructure (e.g. roads, settlements).	• RISICO, a quasi-physical system to predict daily fire danger. • ML algorithm to generate susceptibility maps and hazard maps used for both daily risk assessment, and static maps.	• RISICO: Modelled estimates (hourly and daily) of future dead vegetation fuel moisture content, potential fire spread and intensity. The outputs are adjusted by the ML susceptibility map to avoid overshoot of danger in non-fire prone areas. • Susceptibility and static hazard maps to populate the MyDEWETRA web visualiser. • Forest Fire Early Warning Bulletin edited in MyDEWETRA and sent to Telegram group/channel and mailing list.

A key component of the project was to train forestry staff from the EFCCC to gather and interpret relevant data from MyDEWETRA and RISICO, use the early warning bulletin and analyse hazard maps to predict what may occur in the coming days. Recognising the weather parameters that affect the risk of fires has encouraged trained staff to engage with agencies such as the Ethiopia Meteorological Institute to fact check the information they receive, obtain further information and engage with the EDRMC, the implementing partner for RISICO/myDEWETRA, and first responders as needed.

Results and outlook

The year-long project was successful in developing an information management system for early warning of forest fires in Ethiopia. As well as adapting the Italian model to the Ethiopian context, capacity building and SOPs for the system have also been implemented. With the system now in operation, the Italian Agency for Development Cooperation (AICS) plans to extend it beyond forest fires and create a multi-hazard early warning system (EWS) that incorporates floods and droughts.[56]

55 From the National Centers for Environmental Prediction (NCEP) website: "The Global Forecast System (GFS) is a National Centers for Environmental Prediction (NCEP) weather forecast model that generates data for dozens of atmospheric and land-soil variables, including temperatures, winds, precipitation, soil moisture, and atmospheric ozone concentration. The system couples four separate models (atmosphere, ocean model, land/soil model, and sea ice) that work together to accurately depict weather conditions."

56 UNDRR. (29 November 2021). Exit Workshop on DRR Capacity Building in Ethiopia: Outcomes and Way Forward.

SERVIR Hindu Kush Himalaya in Nepal

Approximately 40% of Nepal's land area is covered in forests, supporting nearly 80% of the population who rely on the forest for timber, grazing livestock and fuel. Between 2001 and 2019, Nepal experienced more than 38,000 fire outbreaks, a number that surges every year with increasingly hot and dry conditions.[57] In 2019, the SERVIR Forest Fire Detection and Monitoring System (SERVIR-HKH) was launched in Nepal.[58]

Figure 9

Partners and their roles in SERVIR-HKH Nepal

Technical partners	Data Partner	Development Partner	Key public sector authority
International Centre for Integrated Mountain Development (ICIMOD)	NASA	NASA	Nepal Ministry of Forests and Environment, Department of Forests and Soil Conservation
United States Agency for International Development (USAID)			

Objective

The goal of the SERVIR-HKH initiative is to enhance fire risk prediction, detection and management in Nepal's Hindu Kush forests.

Process

ICIMOD's system integrates active fire data from the MODIS sensors aboard NASA's Terra and Aqua satellites, facilitated by NASA's fire detection algorithm. Local data, such as forest administrative units and topography, is also integrated to provide active fire data information to a control centre managed by the Department of Forests and Soil Conservation through a web-based dashboard. This dashboard provides information on historical and near-real time fires captured via MODIS.

When a fire is detected, the system automatically sends alerts to around 200 subscribers via email, and an additional 200 forestry officers via SMS. To improve the accuracy of detection, in the second stage of development, ICIMOD integrated data from VIIRS, the sensor on NASA's Suomi satellite, to supplement MODIS data and enhance image resolution.[59]

The system was also extended to enable forest fire risk prediction based on weather forecasts using the High Impact Weather Assessment Toolkit (HIWAT), developed by NASA under the SERVIR initiative and customised for Nepal through a collaboration of ICIMOD and academic partners. Together with national stakeholders, HIWAT predictions are validated using local and national data sources. Various public sector organisations, including the Department of Hydrology and Meteorology, the Armed Police Force, the Disaster Management Training School and Practical Action in Nepal, have received training in using the system.[60]

Results and outlook

The SERVIR-HKH initiative is now a key resource for forest fire management in Nepal.[61] It provides the National Disaster Risk Reduction and Management Authority (NDRRMA) with near-real time oversight of forest fires to understand which districts are most vulnerable. In May 2019, more than 200 fire alerts were sent to district officials, allowing rapid action to be taken. In the first half of 2023, Nepal experienced

57 ICIMOD. (n.d.). Putting out fires: Predicting and curbing forest fire damages in Nepal.
58 SERVIR. (n.d.). High Impact Weather Assessment Toolkit (HIWAT) - Nepal.
59 ICIMOD. (2019). Forest Fire Detection and Monitoring System in Nepal.
60 Government of Nepal, Ministry of Forests and Environment. Forest Fire Detection and Monitoring System in Nepal dashboard.
61 ICIMOD. (n.d.). Putting out fires: Predicting and curbing forest fire damages in Nepal. (Accessed 18 March 2024).

a staggering 118% increase in forest fires compared to all of 2022. In response, ICIMOD strengthened the fire detection and monitoring system by developing a two-day fire risk index using HIWAT. The index provides a general assessment of risks across Nepal's forests, enabling forest fire managers to take mitigation measures and allocate extra resources in advance.[62]

The examples presented in this section showcase the variety of technologies and AI-based models available for predicting, preventing, managing and responding to forest fires, as well as the range of resources and capacities needed to deploy and oversee these systems in different contexts.

In the following section, we identify which AI-enabled tools would be most pertinent for adoption in Pakistan to manage forest fires in the province of KP and the Islamabad Capital Territory given the unique features of the forests, the causes of forest fires and available data, technical and financial resources. Given that Pakistan's forest communities own and manage part of the forest and derive their livelihoods from it, we also highlight the importance of community buy-in for such a system.

While the section discusses Pakistan specifically, our proposed approach to the adoption of an AI-enabled system, and the capacity building to enable it, can be applied in many other LMICs grappling with natural disasters such as forest fires.

Key Insights

The examples provided in this section highlight the importance of tailored approaches that consider various factors such as local context, data availability, funding, and technical capacity. While there isn't a one-size-fits-all model, integrating AI into existing forest fire systems has proven beneficial across different contexts.

Partnerships play a crucial role in the success of AI-driven forest fire management initiatives. Collaborations between data and technology partners, development agencies, and the public sector can leverage each party's strengths and resources effectively. Data and technology partners bring expertise in AI algorithms, data analysis, and technology development. Development partners may provide funding, support capacity building efforts, and offer technical assistance. Meanwhile, the public sector contributes domain knowledge, access to relevant data sources, and leads on actions necessary for implementation.

62 SERVIR Global. (20 July 2023). "Fortifying Forest Fire Forecasting in Nepal". Climate Links.

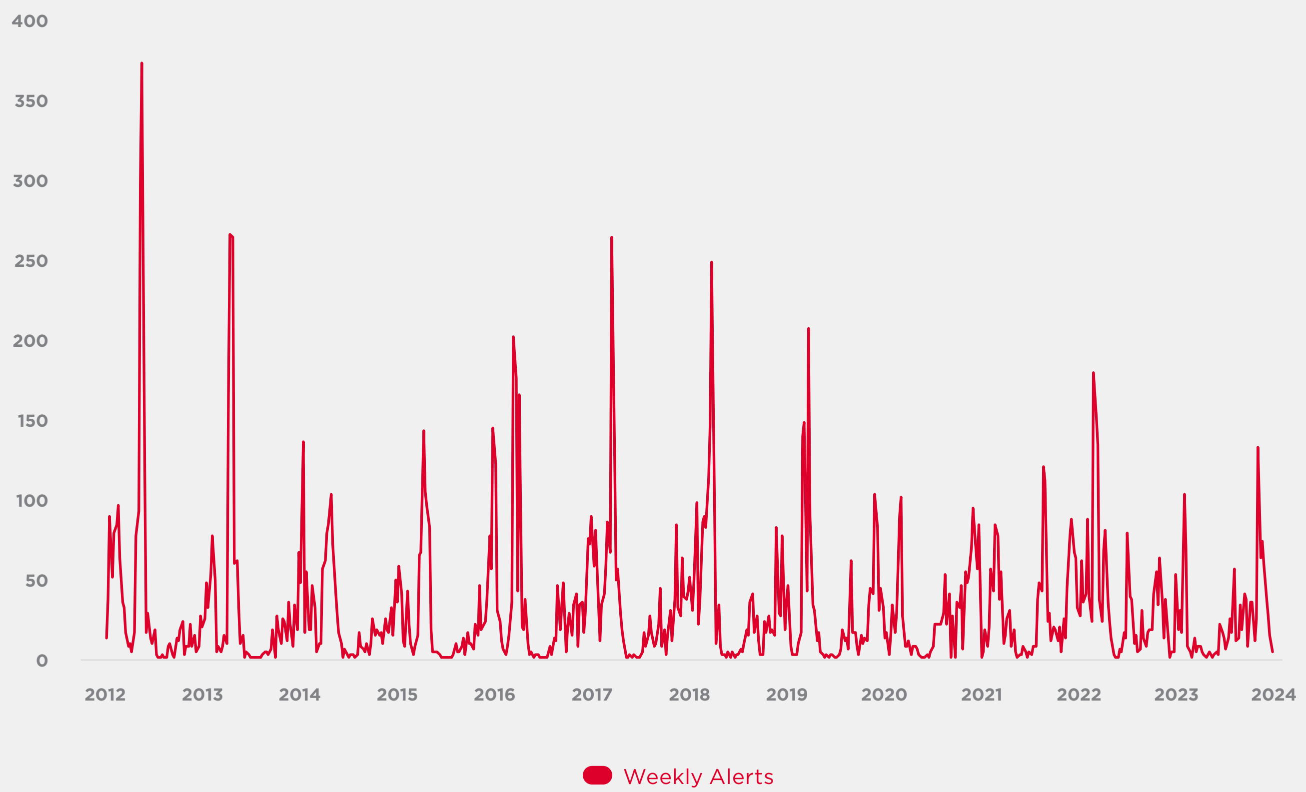
06.
Deploying an AI-enabled forest fire management system in Pakistan

Pakistan is an arid country, with just over 5% of total land area covered by forests, compared to a global average of 33%. The country is experiencing high rates of deforestation that have resulted in soil erosion and landslides and intensified the impact of floods, creating a cycle of worsening natural disaster risks. Between 2001 and 2019, almost 18,000 fire events were detected in Pakistan.[63]

While most fires have been low-intensity ground and bush fires, with the climate getting hotter and drier, and a reduction in traditional practices that reduce fuel load (pine needles) on the ground, the risk of high-intensity fires is increasing. The experience of the Sherani crown fires in 2022 indicates the persistent risk of a blaze spreading out of control.

Figure 10

High confidence forest fire alerts from 2012–2024 based on VIIRS* data



*Visible Infrared Imaging Radiometer Suite
Source: Global Forest Watch[64]

63 Data on fire events is from NASA's MODIS/VIIRS Fire Information for Resource Management System (FIRMS).
64 Global Forest Watch. (2024). Country Dashboards: Pakistan.

Focus regions: Khyber Pakhtunkhwa and the Islamabad Capital Territory

The focus regions in our study include the forests of KP, which cover an area of just over 1.2 million hectares, approximately 45% of Pakistan's total forested area, according to the Forest Institute in Peshawar (Figure 11). The forests comprise both mountainous and temperate forests. The ecology and topography varies, from the Hindu Kush mountain range in the north to the plains in the south of the province. While high-altitude forests have low vegetation, at approximately 3,500 metres above sea level lie alpine forests and more temperate forests at even lower elevations. This varied topography, weather and vegetation have different impacts on the risk and outbreak of fires, with the forested areas covered in chir pine posing posing the highest risk due to the pine needles that accumulate on the forest floor and increase the fuel load.

Figure 11

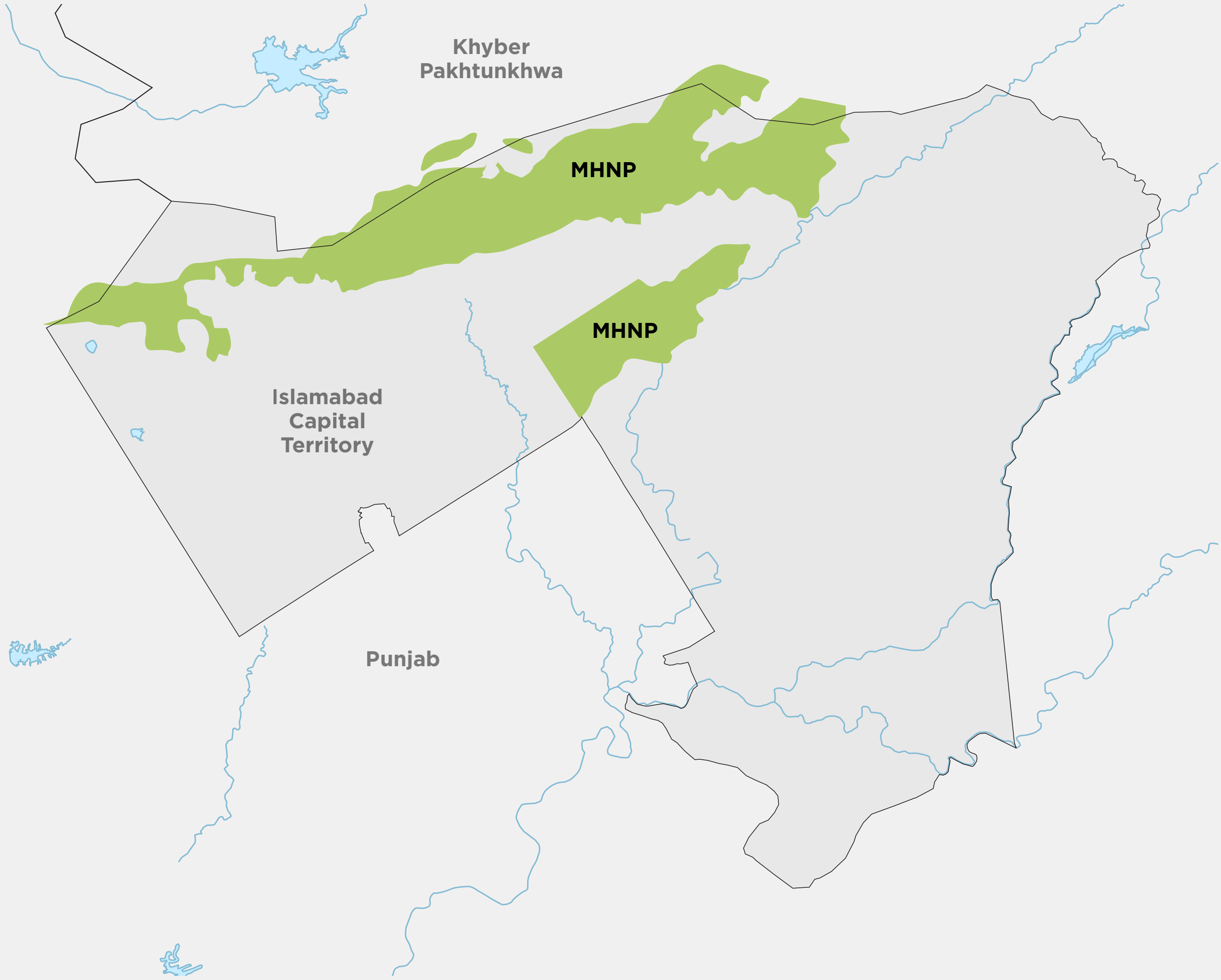
Map of the Khyber Pakhtunkhwa forest, Pakistan

Source: KP Forest Department

Situated within the Islamabad Capital Territory (ICT) of Pakistan, the Margalla Hills National Park (MHNP) covers an area of just over 17,000 hectares (Figure 12).

Figure 12

Map of Margalla Hills National Park (MHNP)



Source: Capital Development Authority, Islamabad

The hills lie at the base of the Himalayas mountain range and have peaks and valleys at an elevation of between 685 and 1,604 metres above sea level. The forest vegetation in the MHNP is mainly of two types: deciduous scrub forest and coniferous pine forest, each of which affect the risk of fires differently. Notable fires have broken out with increasing frequency in the MHNP in the past three years, putting villages and wildlife in the region at risk.

Forest management: key actors

Forest management in Pakistan is decentralised, overseen primarily at the provincial level, although the federal government holds convening power and limited oversight.

The forested areas of KP and the Islamabad Capital Territory are managed differently. KP has a provincial structure while the MHNP in ICT is overseen by the federal government.

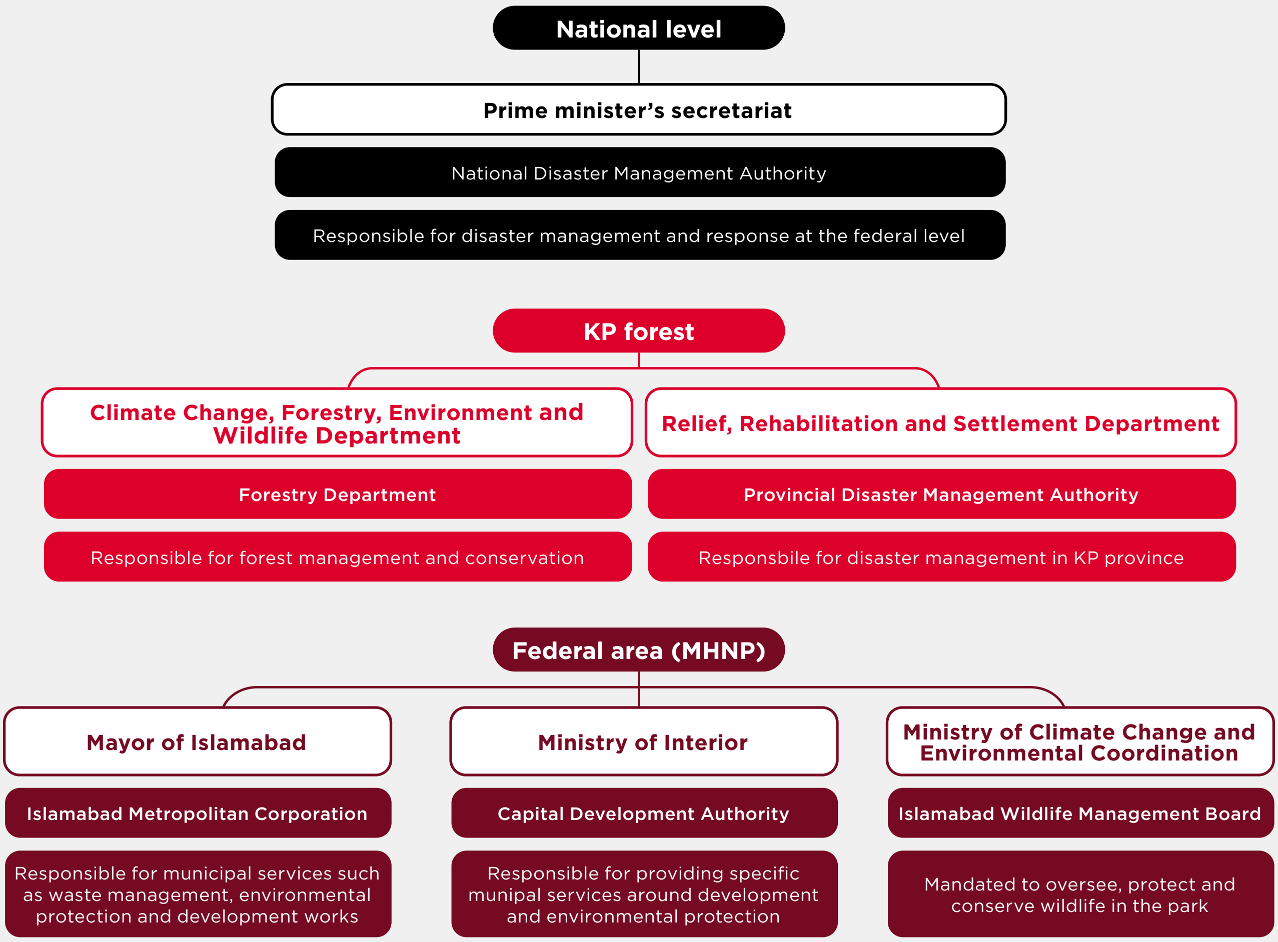
In KP, forested areas are categorised into those "owned" by the government, those allocated to the community for their livelihoods, referred to as guzara, and privately owned land. Agricultural communities within the forests light fire for household tasks and to enhance the fertility of grazing areas.

KP forests are overseen by the provincial Department of Forestry, Environment and Wildlife. The forest is managed by three chief conservators who are each responsible for a specific region of the forest and manage district forest officers (DFOs).

The MHNP is managed by the Capital Development Authority (CDA) with the Islamabad Wildlife Management Board (IWMB) playing an advisory role and providing oversight. The Islamabad Metropolitan Corporation, established under the local government to provide municipal services also plays a limited role in the management of the park. A number of villages are part of the park area, parts of which weave through the federal capital.[65]

Figure 13

Key public sector actors in forest fire management in Pakistan



Source: GSMA Mobile for Development

65 Butt, T. (18 January 2022). "Who owns the Margalla Hills National Park?" The News.

Current forest fire management practices

Forest fire management in Pakistan still relies primarily on manual practices.

Prediction and prevention

Process: Given the lack of sufficient recorded data, forestry officials rely on experiential knowledge to predict fires. To predict high-risk fire seasons and high-risk regions within the forests, they use historical insights from basic data files combined with an awareness of drier and hotter conditions, assessments of ground fuel loads and expectations of human activities, such as agricultural burning by forest communities and tourist-related activities.

In terms of prevention, in addition to maintaining forest fire lines to prevent the spread of fire from one area to other another, forest officers may carry out controlled burns to reduce the combustible fuel load on the forest floor.

Challenges: Despite the wealth of experiential knowledge held by DFOs, the current approach to risk assessments lacks systematic rigour and robustness. Fire outbreaks are contingent on numerous parameters and are challenging for the human brain to comprehensively compute. More rigorous methods of calculating fire risk using technological advancements could significantly reduce the incidence of fires.

Forest officers have also reduced the practice of controlled burns, even as they deem it important, due to the concern a fire may unexpectedly spread and become uncontrollable, especially in very hot weather.

Detection and management

Process: At present, DFOs, along with additional personnel recruited from local communities during high-risk fire seasons, conduct patrols in the forests. The first indication of a potentially spreading fire is the sight of rising smoke. Residents of forest communities, hikers, tourists and individuals travelling on roads through forested regions may also report fires when they observe smoke.

State-owned forest areas are mapped and subdivided into compartments. Each forest area is assigned a unique identifier, and natural features such as cliffs or water bodies are used to delineate boundaries. Patrol officers and local communities are familiar with compartment numbers, enabling them to provide an approximate location of a fire. Similarly, forest areas allocated to the community (Guzara forests) are mapped, and if a fire is detected, reporting includes the name of the landowner to identify the location. No technologies are currently deployed to detect fires. Some fixed infrastructure, such as fire towers, give DFOs a better vantage point to monitor fires, but these are not necessarily located in high-risk areas.

Challenges: Reliance on human patrols for fire detection may lead to oversight in inaccessible areas. There are also an insufficient number of patrol officers, and many are hired only seasonally when risk of fire is high. This makes regular patrols in under-resourced areas increasingly challenging. Additionally, the detection of a fire depends on a visible degree of rising smoke, which may result in notable fire spread by the time it is identified. This increases the risk of wildfires, as the earlier a fire is detected, the less likely it will spread.

Detection alerts

Process: Upon spotting smoke, fire alerts are typically communicated through mobile phones by forest officials to DFOs, who may then escalate the report to provincial managers based on firefighting resource requirements. WhatsApp alerts may also be issued for significant fires that require notification of numerous stakeholders.

Challenges: Some areas of the forests have poor network connectivity, and if a patrol officer's mobile phone battery is depleted, they will be unable to report. In such cases, the report is delivered on foot or via available public transport, resulting in valuable lost time. If a manager misses a call, this can also lead to delayed response and hinder efforts to mitigate the fire before it spreads.

Response and regeneration

Response

Process: Current efforts to combat forest fires employ traditional methods, including brush beating by patrol officers and community members, who often lack equipment or firefighting training. In certain instances, fire extinguishing balls may be deployed.

Challenges: While traditional methods can be effective for small fires, they prove inadequate once blazes spread. Challenges arise when attempting to transport water uphill to forested areas due to the gradient, poor road infrastructure, the weight of water tankers and their limited tolerance to the heat generated by forest fires. Due to limited human and technical firefighting resources, there are no clear plans of action to combat a spreading fire. Predicting how a fire will behave or spread is also difficult, making it challenging to plan evacuations in advance or cordon off at-risk areas. Managing a spreading fire remains one of the most significant challenges.

Regeneration

Process: Although fire damage assessment maps are created from a visual estimate of damage, these are approximations and may not reflect the actual damage caused. Forestry departments also do not have specific initiatives to regenerate burnt areas. The prevalent chir pine vegetation usually regenerates, however, contributing to the reforestation of burnt areas.

Challenges: The lack of a systematic study or assessment of damage and regeneration hamper informed and more extensive reforestation of burnt areas.

Strengthening forest fire management with AI

To address the limitations of the current fire management system, Pakistan could benefit substantially from implementing an AI-enabled forest fire management system. This would help to improve fire prediction and detection and issue early warnings faster. AI could also help to manage a fire by predicting its spread and intensity with a high degree of accuracy, enabling safety measures to be taken in a timely manner and reducing the risk to communities and wildlife. AI could also play a role in damage assessments and regeneration efforts.

There is no one-size-fits-all approach to implementing an AI system for forest fire management. Especially in LMICs such as Pakistan, the implementation of an AI-enabled wildfire management system would require a multi-stage approach that is both sustainable and suited to the context (Table 4). An initial phase could involve modelling fire risk and improving fire detection using satellite-based and open-source data, as in the case of Nepal (see section 5). In subsequent stages, technologies such as IoT sensors and cameras could be deployed to generate additional data. This would enhance the precision of the system as resources become available, and technical expertise, organisational capacity and commitment and community buy-in increase.

Table 4:

Rolling out a staged AI-enabled system for forest fire management in Pakistan

Stage	Activity	Outcome	Benefits	Limitations
1	**AI modelling using remote-sensing data from satellite imagery and open-source data for weather and social data (data on the location of communities, population density, etc.)**	Risk prediction	**Cost effective.** **Can experiment with and refine algorithms using available data**	Accuracy is limited due to low spatial and temporal resolution of satellite data. Other open-source data may compensate somewhat for this limitation depending on availability Lack of “ground truthing” data, i.e data from the field that can confirm the accuracy of remotely sensed data, poses a challenge in assessing model accuracy
	Consistent monitoring of satellite data for detected fires	Detection	**Can detect fires in remote and poorly patrolled areas**	Access to cloud services is needed to store and process large amounts of data A lag of some hours in satellite imagery means that some fires could spread before they are detected High technical expertise
2	**Deployment of IoT sensors and optical/ thermal imaging cameras**	Early detection and management of fires	**Enables early detection of relevant, high-risk fires, minimising large fires and enabling limited resources to be urgently directed to areas of need, minimising loss**	High cost Requires maintenance May require permissions for deployment depending on land ownership/management A local image library of fires and smoke is needed to train the model effectively, but these are not currently available
3	**Add other pertinent layers of data to improve the model, including crowdsourced data**	A robust AI model that can be relied on for risk prediction and detection with a high degree of accuracy and low false positives	**The risk of fire outbreaks is minimised, small fires are combatted quickly before they escalate and continuous damage assessments of forest land are in place**	Expensive High technical expertise Constant maintenance of the system Ownership by an organisation over the long term Sustained investment in system upgrades and human resources High computing power

Modelled outputs in AI-enabled forest fire systems are delivered via a central dashboard that provide multiple outputs such as risk maps, post-fire analysis, fire detection analysis and post-fire damage assessment reports (Figure 14).

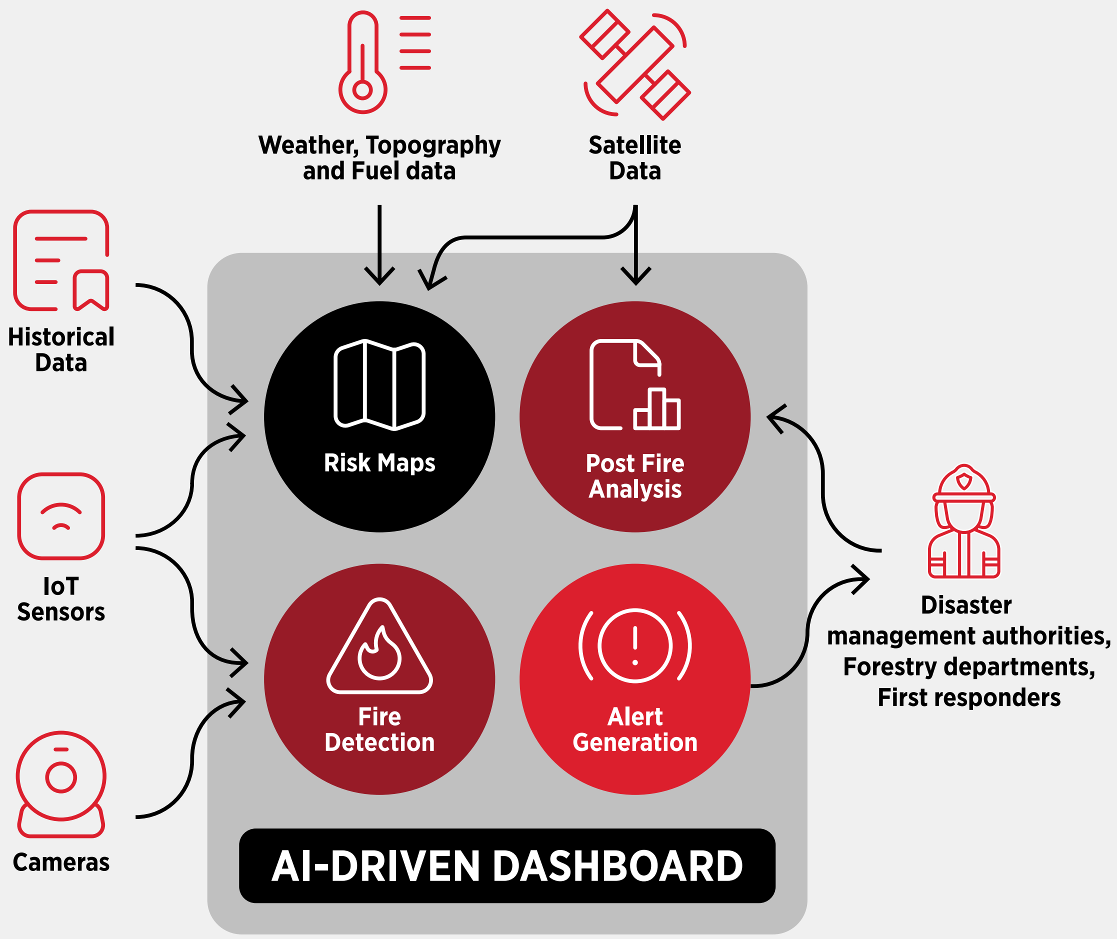
Through the dashboard, different organisations involved in forest fire management can be engaged at different stages of prediction, management and response and collaborate to protect forests. Such a system requires clear offline operating procedures for firefighting, including a chain of command for actions for high-risk situations, early warning of outbreaks and response coordination.

In Pakistan, the National Disaster Management Authority (NDMA) has a significant opportunity within its mandate to either lead or facilitate AI-enabled disaster reduction and response efforts at the federal level, working with provincial disaster management authorities. Collaboration with diverse stakeholders such as forestry departments, data and technology providers, development agencies, and forest communities will ensure that a robust, inclusive system is delivered.

As an alternative, such an initiative could be trialled at an academic institution or by a private sector organisation, and shared with the public sector for adoption once developed, but in all cases, buy-in of and adoption by disaster management authorities and forestry departments would be crucial to its success in transforming forest fire management.

Figure 14

A comprehensive AI-enabled system for fire risk mapping, early detection, management and response



Source: Nature Clicks Institute

Box 5:

AI for forest fire management in Pakistan: a pilot project

A pilot project funded by the UK Foreign, Commonwealth & Development Office (FCDO) and UK Frontier Tech Hub, is currently being conducted by the Lahore University of Management Sciences (LUMS) and the World Wildlife Fund (WWF). The pilot implements an AI-enabled system for early forest fire detection and risk assessment in one site of the KP forest and is the first AI-enabled fire management system to be deployed in Pakistan, integrating multiple technologies for risk prediction and early detection.

An AI-powered camera that transmits images in real-time is the primary tool for fire detection over a vast forested area. A PTZ camera has been deployed as a cost-effective, low-maintenance solution and enhanced with AI capabilities to detect the onset of a fire event.

Satellite-based images are also being used to create scaled maps of the forest to determine soil moisture, fuel load, dryness and other relevant parameters.

LUMS/WWF have also deployed automatic weather stations to collect data. These IoT-enabled stations send real-time data on essential weather parameters such as temperature, humidity, wind speed and soil moisture. This data can be used for ground truthing, or verification, of the data collected from satellite imagery, as the latter can have low spatial and temporal resolution.

IoT fire detection sensors have also been deployed to enhance the features of the EWS. IoT sensors offer increased detection capability at a more granular level.

Once the model is fine-tuned to a high degree of predictive and detection accuracy, it could play a valuable role in a larger-scale roll out.

Transitioning to an AI-enabled system: readiness assessment

In this section, we discuss Pakistan's readiness to implement an AI-based forest fire management system. Drawing on interviews with 25 sector experts in the country, we consider key factors such as data availability and useability, stakeholder coordination, institutional capacity, sustainable finance and community inclusion.

Data

Data availability

Several national organisations hold relevant data that would be valuable in building and refining an AI model for forest fire management for Pakistan. The Space & Upper Atmosphere Research Commission (SUPARCO) and the Pakistan Meteorological Department are key sources of satellite imagery and meteorological data. The NDMA is already integrating data from these organisations to predict the risk of floods and landslides, and aims to integrate fire risk modelling in their initiatives.

The Ministry of Climate Change and Environmental Coordination has established a National Forest Management System (NFMS) that provides spatial and statistical data on forests, primarily providing data on environmental conditions such as carbon stocks and emissions. The NFMS has been designated as the central repository for all information linked to the national REDD+ programme.[66] REDD+ is a framework established to protect forests globally and reduce deforestation as part of the Paris Agreement, and each country must propose a plan and set of targets to meet. The NFMS initiative proposes a satellite land monitoring system (SLMS) to monitor and regenerate forests, and has already conducted extensive work on available satellite data and the division of forests into administrative units for analysis and classification of vegetation. This data could be leveraged for an AI-enabled forest fire management system and the two initiatives could work together to improve overall capacity in the management and conservation of forests.

The recently established Land Integration Management System (LIMS) has developed a platform to improve agricultural production using data-based approaches, and is analysing weather and soil data to provide more than 20,000 farmers in the Punjab with tailored information to optimise production. LIMS could also play a role in providing data for forest fire management, although it is not currently monitoring forests specifically.

The Pakistan Bureau of Statistics holds data on settlements that could also be integrated in the modelling to account for the impact of community presence or human activity on fire risk, and inform response and evacuation efforts in the case of a spreading fire event.

There are also international and national commercial sources of data that could be used, depending on sustainable funding. Agritechs such as Pakistan Agriculture Research[67] and Farm Dynamics have deployed weather stations that generate data for improved agriculture and could extend their reach to provide this data for forested areas. Similarly, Crop2X is a GSMA Innovation Fund grantee[68] that utilises Internet of Things (IoT) sensors and satellite imagery to provide farmers in Pakistan with real-time data, and could provide services for DRR.

The KP Forest Department has standard procedures for recording forest fire incidents as well as forest fire outbreak records spanning decades. This data is currently recorded primarily in soft copy formats and includes the location, size and cause of fires. These records could be digitised to inform the modelling.

As noted earlier, sourcing local photographic images of hazards to train an AI algorithm is particularly challenging as it is not an everyday occurrence and events are few and far between. There is an opportunity to crowdsource image data to accelerate the training of the AI model for forest fire management, which could be particularly useful in a setting such as Pakistan where historical data on fires is not extensive and not yet digitised. Using a smartphone app and/or a website, local communities, hikers and tourists could upload real-time images of fires and smouldering vegetation that could be fed into the model to improve prediction and classification. Crowdsourcing could also be used to assist in data collection after a fire event, particularly from camera blind spots and in hard-to-reach areas, to assess the extent of damage. Human-in-the-loop Project Dorian (see Box 6) is a good example of the value of crowdsourcing data for post-natural disaster damage assessments.

66 Ministry of Climate Change, Government of Pakistan. (2020). Develop Forest Reference Emission Levels/Forest Reference Level and National Forest Monitoring System, Measurement, Reporting and Verification System for REDD+.

67 Pakistan Agriculture Research is an agritech providing verified and accurate data to farmers for data-based decision making. See website.

68 GSMA. Digital Grantees Portfolio.

Box 6:

Crowdsourcing data to build better AI algorithms for natural disaster management

Human-in-the-loop Project Dorian, implemented by the Qatar Computing Research Institute, is proof of concept of the value of crowdsourcing for damage assessment.[69] The AI system scanned and filtered social media images following Hurricane Dorian in the Bahamas. The algorithm then ranked the images based on severity of damage, which formed the rapid damage assessment. Through a human-in-the-loop participatory approach, whereby humans are interactively and iteratively involved in model development, members of the emergency response team were trained on how to verify the severity labels assigned by the algorithm. This approach led to improved reiterations of the AI algorithm by identifying common errors. It also provided the algorithm a novel image dataset with verified severity labels, which were used to further train the model and improve its accuracy. While this application focused on damage from landfall of a hurricane, it demonstrates the value of crowdsourcing data for damage assessment, which can be applied to other stages of disaster risk management.

Data useability

The structure, quality, completeness and format of data is integral to assessing its useability, which would need to be done at the modelling stage.

Establishing data standards and providing forestry departments and disaster management authorities with training on the quality and format of data collection needed for modelling is an important step in enabling more accurate prediction and detection models. In this regard, international data standards could inform national standards and be adapted to the local context where needed. Given the nascency of AI for disaster risk management, these standards are still being established at the global level. In 2021, the International Telecommunication Union (ITU), the World Meteorological Organisation (WMO) and the United Nations Environmental Programme (UNEP) established a focus group on AI for Natural Disaster Management (FG-AI4NDM) that brings together experts from many fields to produce data standards to inform AI algorithms for natural disaster management. It has proposed three standards that are currently under review by ITU member states.[70]

Capacity building on how to collect and store data using standards that can support algorithm development is much needed to support data providers in Pakistan's public, private and academic sectors.

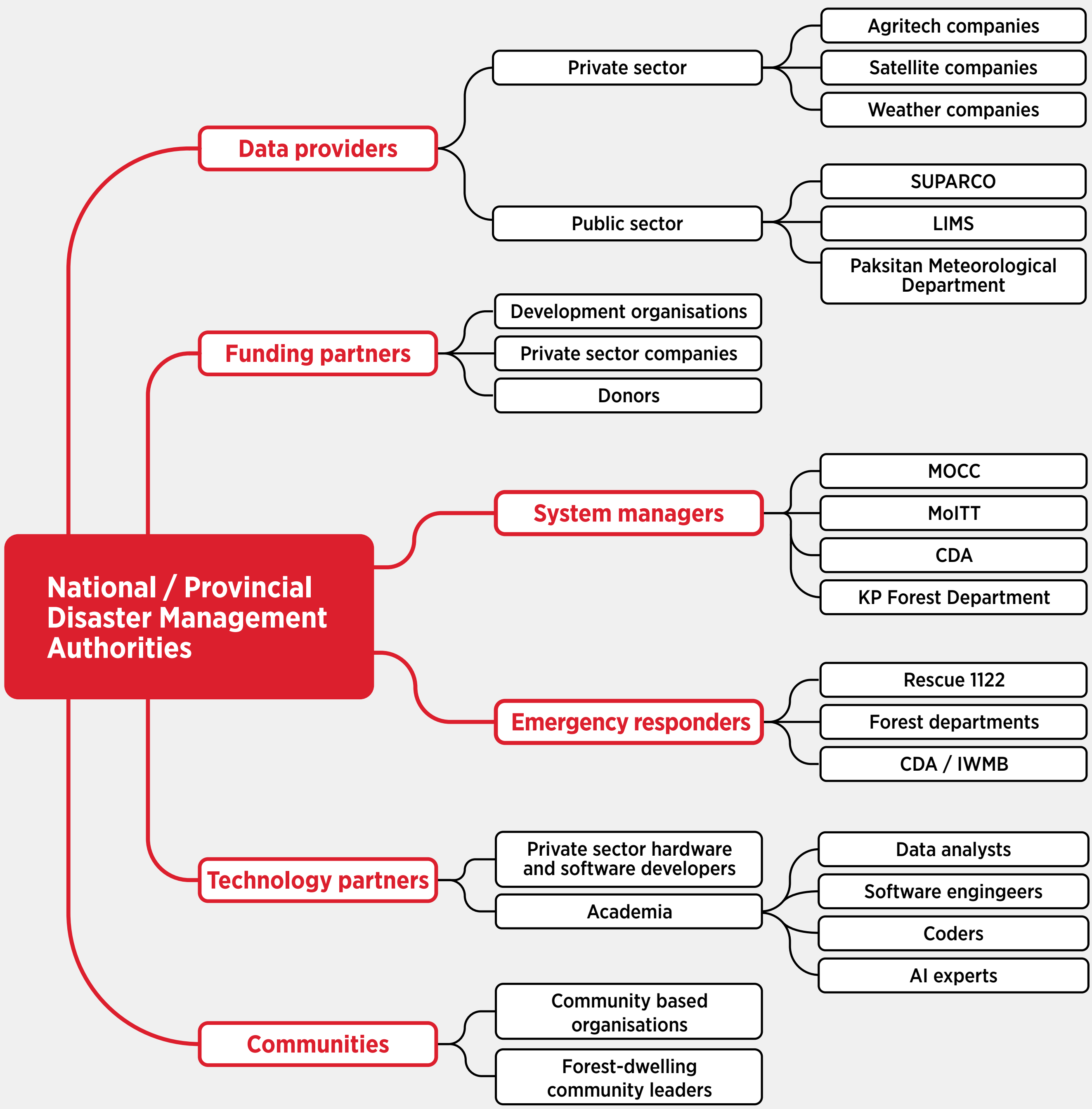
69 Nesta. (2021). Participatory AI for humanitarian innovation: A briefing paper.
70 Kuglitsch, M. and Stern, E. (27 October 2023). "Focus Group Facilitates the Use of AI for Natural Disaster Management". ERCIM News.

Stakeholder coordination

Stakeholder coordination is essential for building, scaling and sustaining AI-enabled forest fire management systems. A collaborative effort involving public and private sector organisations, federal and provincial agencies and academia is needed to build an effective system across Pakistan's provinces and at the national level (Figure 15).

Figure 15

Key stakeholders in the deployment of an AI-enabled wildfire system



Source: NCI/GSMA Mobile for Development

Humanitarian agencies, community-based NGOs and forest-dwelling communities in Pakistan are integral in detecting, managing and delivering early warnings of forest fires and should be part of any AI-enabled solution. For instance, the WWF has been monitoring Pakistan's forests for many years and could engage communities in fire prevention and warning dissemination. Forest-dwelling communities are legally obligated to provide support in extinguishing forest fires and have a significant stake in forest fire management, making their involvement essential for comprehensive and effective incident management and ensuring lives are protected.

Like other LMICs, Pakistan faces challenges coordinating the efforts of different institutions, which is exacerbated by limited federal authority over provincial forest management. In Pakistan, managing natural disasters requires a cohesive and integrated approach, and robust coordination mechanisms between key entities such as the NDMA, KP Provincial Disaster Management Authority (PDMA) and KP Forest Department for KP forests, and the NDMA, CDA and IWMB for forests in the MHNP.

In Pakistan, the involvement of multiple organisations in managing areas like the MHNP poses the risk of a fragmented approach or potential overreach, leading to additional coordination hurdles. The CDA is under the purview of the Ministry of Interior while the IWMB operates under the Ministry of Climate Change, necessitating coordination and agreement between the two ministries about their role in forest fire management in the MHNP. In addition, the Metropolitan Corporation Islamabad (MCI), which also oversees municipal works in the ICT, operates under the city government, adding complexity to the administrative management of the MHNP.

Furthermore, close coordination between forestry departments, PDMA and NDMA is essential to ensure early warnings reach first responders and community organisations effectively. Presently, public sector bodies operate independently, adhering to their mandates and missing out on opportunities for collaborative efforts to bolster disaster management systems. This lack of collaboration extends to data and knowledge sharing.

To address these administrative and jurisdictional challenges, and lack of collaboration with the private sector, a re-evaluation of organisational coordination is needed. Moreover, enhancing collaboration with forest-dwelling communities and first responders is vital for a comprehensive and efficient AI-enabled disaster management framework.

Institutional capacity

A variety of institutional capacities are needed to develop and maintain a tech-enabled disaster management system, including:

- Sufficient human resources
- Technical capacity and skills
- Financial resources

Our assessment of these capacities in Pakistan in conversation with many experts, as well as a review of existing documentation, revealed the following findings.

There is a lack of institutional capacity in many public sector organisations, which is complicated by persistent political uncertainty that threatens the continuity of existing initiatives. No prime minister in Pakistan has completed a full term in office, and each new government sets new or alters existing priorities and agendas. Each election also delays approval processes, slowing public sector initiatives.

Budget constraints severely limit the human resources that disaster management organisations and forestry departments can employ. There is not enough staff at any level. For example, in the KP Forest Department, of 7,281 sanctioned personnel, 2,553 positions were recently reported vacant. Human resources are lacking across the board, from insufficient patrol officers on the ground to data analysts and modellers required to build AI algorithms for forest fire management.

Private sector tech companies are limited both by the capital they can raise and the price they can charge for their services, especially when serving a constrained public sector. There is also the challenge of continuity of projects under public-private partnerships (PPPs) when governments change.

More personnel with the right skills are needed at all tiers of disaster management in Pakistan's public sector, as well as guaranteed long-term funding to retain and incentivise trained staff.

Developing models

Developing the multi-stage, AI-enabled system outlined earlier depends heavily on technical capacity, particularly the expertise of experienced AI professionals.

Pakistan has a strong IT services industry, with companies providing software development, outsourcing and IT consulting services to clients worldwide. Despite notable engineering programmes and higher education institutions, there remains an overall scarcity of technical talent in data analytics and data engineering. Every year, there are approximately 25,000 engineering and 35,000 computer science graduates, but many lack foundational computer science knowledge. Only a small percentage that graduate from elite higher education institutions are equipped with the requisite skills. The growing number of software companies grapple with recruiting adequately skilled employees.

As a result, only a select few academic institutions and private enterprises have the technical prowess to develop the algorithms essential for a comprehensive AI-enabled forest fire management system. Engaging with higher education establishments offering software IT and engineering degrees to encourage research centres in disaster risk prediction and management could significantly strengthen the country's capacity in this regard, especially given Pakistan's high risk of natural disasters.

GIS capabilities

In the context of an AI-enabled system, the dashboard providing risk maps and early warnings overlays a GIS, which integrates descriptive information with geographical maps, incorporating location data. GIS mapping is used extensively in Pakistan in sectors such as urban planning, agriculture, natural resource management and natural disaster response.

Regarding key stakeholders in an AI-enabled forest fire management system, the CDA has robust GIS mapping capabilities and the KP Forest Department houses a GIS lab, but there is a shortage of skilled personnel. Despite having five sanctioned GIS managers, nine sanctioned GIS specialists and 11 GIS analysts, only one GIS role is presently filled at the KP Forest Department. Hence, there is an urgent need to improve GIS capacities. In a quick survey of capacities with 30 DFOs in KP, just over 30% reported having received basic GIS training, and more than 97% reported having a desktop computer at their office, but all reported keeping only manual records of forest fires.

Expanding the capabilities of both these departments could facilitate digital mapping of forest fires and help to develop more precise algorithms. Moreover, numerous NGOs, private entities and academic research labs possess GIS capabilities, signifying readily available GIS skills within the country. Enhancing the capacities of forestry departments through regular training in collaboration with these organisations can facilitate the complete digitisation of forest monitoring and record-keeping, continually enriching the model.

Response capabilities

In terms of first responders, dedicated organisations such as Rescue 1122, forest patrol officers and community responders would all require training and clear SOPs in the event of a fire alert issued by the CDA/IWMB or the KP PDMA. Implementing a top-down alert system from the NDMA to officers and communities, rather than the reverse method now in place, would disrupt existing mechanisms. Retraining and awareness-raising among community members would therefore be crucial.

The Pakistan Forest Institute in Peshawar, the KP Forest School Thai Abbottabad and the Forest Services Academy in Murree could all serve as hubs to offer regular training to DFOs on a tech-enabled system and associated response mechanisms.

It is important to note that while AI can play a pivotal role in mapping fire risks, detecting fires early to mitigate their impact and even aiding fire control by predicting intensity, speed and direction, the expertise of DFOs, trained responders and the invaluable experiential knowledge of communities, should remain central in response efforts. Their knowledge and existing procedures, coupled with the support of community-based organisations, are indispensable in managing fire outbreaks effectively. Rather than seeking to replace them, any AI system should aim to complement and enhance their capabilities.

Sustainable finance

Extending Pakistan's current forest fire management system to an AI-enabled one will require dedicated financial resources. Pakistan faces significant fiscal constraints, with only 10% of GDP generated from taxes and minimal spending on human development with just 1.2% of public expenditure allocated to health and 1.8% to education. Consequently, financial resources for climate action are severely limited.

In formulating a crisis management plan for Pakistan (2023–2025), the UN International Organization for Migration (IOM) estimated that USD 11 million would be needed for adequate disaster preparedness and response, accounting for the risk of multiple disasters.[71] Our proposed multi-stage approach to rolling out an AI-enabled system presents a step-by-step, scalable strategy for system development, ensuring that the necessary funding is secured before progressing to the next level. Given the scale of the project, substantial international financial assistance is likely to be needed to develop and sustain a comprehensive, multi-tech-enabled system operating with a high degree of accuracy.

Experts we consulted for this research indicated that the cost of skilled human resources is likely to far exceed that of technology and maintenance costs of an AI-enabled system, although this depends heavily on the type and amount of technology deployed.

High-income and high-risk countries such as the US, Canada and Australia fund their wildfire management through government budgets. For instance, the US has committed USD 461 million for wildfire mitigation and resilience in 2024.

High risk of forest fires in northern Morocco has led the government to commit USD 22 million to combat forest fires in 2024, with the use of emerging technologies to predict risk and detect fires at early stages integrated in the management plan.

Türkiye's AI-enabled FireAId system (see section 5), which analyses more than 400 variables to predict forest fires, is a strong example of a collaborative, multi-stakeholder model between the private sector (specifically Koç Holdings), the Turkish Ministry of Agriculture and Forestry and the World Economic Forum (which plays an advisory, not a funding role).

Brazil is another country that experiences a high number of forest fires. In 2023, there were 190,000, more than half of which occurred in the Amazon rainforest, burning an astounding 26.4 million acres of forest. Forest fire management in large parts of Brazil is conducted by the private sector. Under a public-private partnership (PPP) model, commercial agricultural company, Sintecsys, has deployed 360-degree cameras mounted on towers and processes these images to detect and issue early alerts for fires.

In most LMICs, funding for AI-enabled forest fire management has been typically provided or enhanced by grant funding from international partners, which may also offer technical support to national and local stakeholders to strengthen risk assessment and mitigation capacities and train forest staff to respond to risk predictions. For instance, USAID and NASA's joint SERVIR initiative (discussed in section 5) supports Nepal in fighting frequent forest fires alongside ICIMOD as the technical partner. Similarly, Ethiopia's deployment of RISICO (also discussed in section 5) has been funded by the Italian Ministry of Foreign Affairs.

To build an AI-enabled forest fire management system and optimise its use, Pakistan will need to identify the right international and local partners to build a sustainable funding pipeline and a robust plan for the long-term continuity of the system, regardless of political changes. Sustained funding will be needed to maintain and upgrade technology deployments, the technical infrastructure needed to collect, store and process data and maintain skilled human resources at every level of the system to constantly improve the modelling and use its results effectively in the field for fire management and response.

71 IOM. (27 November 2023). Pakistan Crisis Response Plan 2023-2025.

Community inclusion

The communities living within the forests of KP and MHNP play a critical role in Pakistan's current forest management system. Most likely to be first responders to a fire, community members use traditional methods to extinguish fires often at risk to their lives. Community members are also hired during fire season to monitor the ignition of fires and the damage from fires affect their livelihoods. Communities may also carry out controlled burns to encourage fresh growth for livestock feed and clear the ground of pine needles, the excess build-up of which are a major fire risk.

While the deployment of an AI-based solution to forest fire management will help to mitigate fire risk, its success depends on effective and sustained community involvement. Lessons on the value of community inclusion from national and international technology interventions for disaster risk management are outlined in the following section.

Incorporating the experiential knowledge of communities

In a collaborative approach to an AI-enabled forest fire management system, the knowledge of the local community can be vital in developing an accurate prediction and classification AI model. As discussed in section 4, AI models require multiple data parameters that are unique to the location and situation. The local community in KP and Islamabad have experiential knowledge of the forests, including the terrain, the predictors and causes of forest fires and methods of fighting fires. This places them in a unique position of understanding fires in a highly localised way, which is valuable for building a successful AI model. Focus group sessions or workshops held with the community and AI architects can help to ensure this knowledge is integrated in AI model development.

The BurnPro3D decision platform is an example of a collaboration project with the local community. Developed by the University of Southern California (USC) Viterbi School of Engineering and the San Diego Supercomputer Center, the platform uses AI to support and enhance Indigenous methods of prescribed burning to fight forest fires.[72] Through a partnership with Indigenous tribes and local firefighters, the researchers built a model that predicts how fires evolve under different conditions. Firefighters can use the insights produced by the model to determine where best to set a prescribed fire and at what intensity, while considering factors such as air quality and protected sites. Nuanced local knowledge shared by the community proved vital in developing this AI-enabled solution, which has improved rather than replaced traditional methods of fighting forest fires. This example has global relevance, as many forests provide key sources of livelihood to forest-dwelling communities that are also their biggest beneficiaries and protectors.

Crowdsourced data

As noted earlier, local communities can play a role in crowdsourcing data to inform AI models as they hold unique experiential knowledge of the forests. This would further invest the community in the ongoing development of the AI solution to strengthen forest fire detection, increase community buy-in and improve the effectiveness and sustainability of the solution.

Opportunities for employment

Community members of the KP and ICT forest regions are hired seasonally to patrol the forest to detect and fight fires. During low-fire risk periods, the locals lose this income as their services are not needed. The deployment of technologies such as cameras and IoT sensors provides the opportunity to permanently employ the local community to maintain and troubleshoot these technologies. This approach has been successfully implemented in the context of AI for flood management, although it was restricted to a voluntary basis.

The Aga Khan Agency for Habitat (AKAH) is currently training local community-based disaster management volunteers in Pakistan to increase preparedness and response to both natural and human-made disasters. In northern Pakistan, this has included the training of volunteers to monitor the health of AI-enabled early warning flood detection systems. Volunteers are trained to clean the solar

72 Dillon, C. and Bumenthal, A. (27 September 2021). "AI to Fight Wildfires". USC Viterbi.

panels, test the technology and make necessary adjustments. This community-based approach to disaster management empowers the community to strengthen their resilience to crisis by developing a range of technical expertise and building trust between the implementers of the technology and the local community.[73] The programme at AKAH has also been vital in upskilling women in both disaster response and tech, who account for more than 50% of the 36,000 community volunteers.

The success of AKAH in engaging the community in the deployment of AI for flood management provides valuable lessons that can be applied in other contexts, such as AI for forest fire management. There is also an opportunity to advance the community-based strategy modelled by AKAH to provide jobs rather than volunteer opportunities, enabling forest-dwelling communities to secure permanent rather than seasonal income.

Addressing concerns through community engagement

Technologies, particularly those associated with surveillance, can evoke suspicion and resistance from local communities. Addressing and incorporating community concerns about technology deployment are pivotal to achieving community buy-in. LUMS/WWF offer a good example of how this can be achieved in the context of an AI deployment for forest fire management in Pakistan (Box 7).

Box 7:

Lessons from the WWF on community engagement

Building trust with communities through open dialogue and active listening is deemed crucial to the long-term success and sustainability of any conservation project.

Agricultural and nomadic communities living in the KP and MHNP forests derive their livelihoods from the forest, and burning old crop to make way for fresh new vegetation for grazing livestock is an old practice in the forests. Community members are therefore compelled to light fires for controlled burning, and the deployment of devices that might identify them leads to suspicion and rejection of such technologies.

In the absence of sensitisation, engagement and awareness-raising around the purpose and use of devices to collect data for an AI-enabled system, communities worry about surveillance. Engagement initiatives empower communities to understand how their lives can be protected from the risks of forest fires and provide a platform for community firefighters to learn how an AI-enabled system can reduce the life-risk of fighting dangerous fires. It is therefore essential that the community is consulted and engaged with prior to any device deployments in the forest.

73 Aga Khan Development Network (AKDN). Pakistan: Disaster Preparedness and Response website.

Other considerations

Connectivity and infrastructure

While consultations with experts did not indicate a lack of connectivity in forests in KP and the ICT as a significant concern, power outages in control and command centres were highlighted as a more significant issue. In areas where connectivity is lacking, the Universal Service Fund (USF) in Pakistan has the mandate to provide connectivity in underserved areas and can offer both investment and guidance on installing IoT devices and cameras based on existing connectivity. In particularly remote areas, connectivity challenges may be addressed using innovations such as LoRaWAN mesh networks. In addition, Pakistan's Ministry of Information Technology and Telecommunication (MoITT) is aiming to improve connectivity via Starlink, a set of low-orbit satellites delivering better broadband connectivity.[74]

Hard infrastructure

For fire observations, cameras need to be placed at a certain height to have a good view of the surrounding landscape. There is currently limited infrastructure on which cameras can be deployed at a suitable height. The Punjab Forest Department has 15 existing fire towers that can be used for infrastructure deployment, but none were reported for KP or MHNP forests, a challenge that will need to be addressed when cameras are deployed for observation.

Box 8:

The role of mobile network operators in an AI-enabled forest fire management system

Mobile network operators (MNOs) can not only help to provide connectivity to an AI-enabled forest fire management system, but also share infrastructure by deploying cameras at a certain height on their towers. However, this is subject to regulations, policies and security considerations, as well as a viable business case.

In Kazakhstan, for example, Beeline Kazakhstan, a subsidiary of the global digital operator VEON, which provides connectivity and online services, has deployed an AI-based forest fire detection system. The system, called Orman-AI, automatically detects fires at an early stage, using cameras with 360-degree vision capabilities and the ability to operate in extreme weather conditions. The cameras are deployed on Beeline's towers and use their mobile connectivity. Data is uploaded in real time to an AI analytics engine trained to detect images of smoke plumes.

In a more advanced use case in the US, the AI company Pano[75] provides near-instant alerts in the case of a fire outbreak using multiple technologies, such as state-of-the-art optical cameras and sensors and satellite data. Pano is collaborating with T-Mobile to use its 5G network capabilities to deploy 5G cameras that can collect and analyse large amounts of data in near-real time to identify fires and issue alerts.

75 See Pano website.

Key Insights

Data

Existing data sources, ranging from satellite data, open global meteorological data, and public and private sector organisations generating data relevant to AI modelling are a good starting point for trialling an AI-enabled system. A foundational step is to identify all relevant data providers from various sectors and build data-sharing partnerships.

In addition, capacity building on how to collect and store data digitally and using standards that can facilitate algorithm development in DRR is much needed to support data providers in Pakistan's public, private and academic sectors.

Stakeholder coordination

Managing forest fires requires a cohesive and integrated approach between different institutions. Coordination between key actors such as federal and provincial disaster management authorities and forest departments, clear administrative jurisdiction over forest management, and a proactive approach to collaboration between the public and private sectors and academia to leverage their unique strengths will help deliver a robust AI-enabled system.

Institutional capacity

Insufficient human resources, limited technical skills and limited budget to train and retain skilled staff, especially in forestry departments, poses a challenge to building a reliable AI-enabled system and embedding its use in DRR. Budget allocations for hiring and retaining sufficient, adequately skilled staff need to be reconsidered.

Sustainable finance

Due to limited fiscal capacity, and competing priorities for federal and provincial funding, DRR remains underfunded. Long-term funding partners are needed to ensure that an adequate AI-enabled system can be built and sustained.

Community inclusion

It is important that key public and private sector actors involved in forest fire management take proactive steps to sensitise forest-dwelling communities to technology-enabled approaches to build trust. A key value add of such engagement is that the local knowledge of forest dwelling communities can help enrich AI models. Communities can be a partner in crowdsourcing data as well as play a role in the maintenance and protection of technologies deployed in the field to gather data and monitor fire events.

Limitations in fundamental enablers of AI systems, which include access to power and connectivity, act as a huge barrier to tech-enabled DRR, and must be addressed as a priority before embarking on system development.

Conclusion and recommendations

Already a forest-poor country, and facing high climate risk, Pakistan stands to gain significantly from more effective forest fire management and broader DRR, leveraging AI. Based on our readiness assessment for Pakistan to strengthen its forest fire management system using AI, we propose the below steps to developing the system, which are applicable in a variety of similar contexts.

Identify the project owner.

Identify key funding partners and ensure that sustainable funding is available for a large-scale roll-out.

Conduct a rapid assessment of fundamental enablers: power, connectivity and ICT infrastructure in departments that the system will inform, and for tech. deployments in the field.

Engage with organisations delivering AI-enabled forest fire management systems in the international context to build knowledge.

Identify local AI, technology and data experts and engage with them to understand data, technology and infrastructure needs.

Identify data providers and form data-sharing partnerships.

Develop a fire risk prediction and detection model based on existing open and commercial data.

Improve the model with strategic technology deployments in the field.

Deliver fire risk prediction and detection via dashboards to central authorities such as disaster management agencies and forestry departments.

Embed information and alerts from the dashboard into standard firefighting SOPs and integrate first responders and community-based NGOs and leaders into the system.

In order to undertake this step-by-step approach, we recommend the following actions to create an enabling environment and build capacity for successful development and deployment of a DRR system specifically for forest fire management.

Table 5:
Strategic priorities for effective AI-enabled forest fire management systems

Prerequisites	Action	Actor
Better co-ordination between key actors involved in forest fire management.	The public sector, in the case of Pakistan federal and provincial disaster management authorities, need to align more closely to establish a shared vision and objectives of an AI-enabled DRR system and their role in its development.	**Disaster management authorities**
	Public and private sector organisations and academia must proactively collaborate with each other on data collection and sharing, technology development and deployment, and algorithm development, based on their particular strengths and capabilities.	**Data partners** **Technology partners** **Disaster management authorities** **Universities with Engineering and Computer Science departments**
	Disaster management authorities, forestry departments and emergency response organisations must co-ordinate more closely with each other to ensure a harmonised response to fire risk alerts and incidents.	**Forestry departments** **Disaster management authorities** **Emergency response organisations**
Sustainable funding and risk mitigation	Sustainable funding sources must be established before scaling an AI-enabled system.	**Project lead** **Development and donor partners**
	A risk mitigation plan should be developed 1) in case of limited or unreliable sources of funding, as well as 2) for maintaining the system regardless of political changes that could impact investment and priorities.	**Project Lead**

Need	Action	Actor
Capacity building	Disaster management authorities and data partners need to build capacity to transition to an AI-enabled system by learning from international deployments.	**Data partners** **International knowledge-sharing partners**
	AI for DRR should be embedded in higher education curriculums in engineering and ICT programmes.	**Institutes of higher education**
	Forestry departments need to improve capacities for digital data collection, GIS and the use of web/mobile based dashboards to understand fire risk and detection.	**Forestry departments**
	Forestry training institutes should embed digital data collection, GIS training and non-technical training on the use of AI in DRR in curriculums.	**Forestry training institutes and departments**
	AI experts should be funded to develop specific technical know-how on AI for DRR.	**Development partners** **Government** **Institutes of higher education**
Identification of key infrastructure gaps	A rapid assessment of gaps in fundamental infrastructure needed for the system, including uninterrupted power, reliable and low latency connectivity, and data storage and compute power, should be undertaken.	**Project lead**
	Key gaps in enabling infrastructure, including consistent power and connectivity, and relevant IT infrastructure such as hardware and software elements needed for AI, should be addressed.	**Project lead** **Energy providers** **Mobile operators** **Technology companies** **Software providers/ developers**
Community engagement	Forestry departments, community-based NGOs and community leaders should remain in dialogue to understand, accept and support an AI-enabled forest fire management system.	**Forestry departments** **Community-based organisations** **Community leaders**

GSMA Head Office
1 Angel Lane
London
EC4R 3AB
United Kingdom
Tel: +44 (0)20 7356 0600