In collaboration with
Deloitte and Koç Holding

WORLD ECONOMIC FORUM

The Next Frontier in Fighting Wildfires: FireAId Pilot and Scaling

INSIGHT REPORT

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Images: Getty Images, Unsplash

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Forewords

Levent Çakıroğlu
Chief Executive Officer,
Koç Holding

One of the most evident consequences of the climate crisis is the increasing occurrence of wildfires across the globe. We all have to acknowledge this harsh reality as a new global challenge and act accordingly. Two years ago, when Türkiye was devastated by the worst wildfires recorded in its history, Koç Holding decided to adopt this longer-term vision and do more than what we had been doing already to alleviate the immediate social and environmental impacts of these disasters.

Embracing digital transformation as the backbone of our business strategies, we wanted to offer our advanced data analytics capacity in the global fight against wildfires in order to prove the huge potential of artificial intelligence in this very specific and significant use case. Being a committed partner of the World Economic Forum, we have formulated this initiative as a collaborative technical assistance project that aligns with the Forum's global mission and problem solution approach.

The FireAId project aims to allow better prediction of wildfires and the more efficient use of resources during firefighting operations. For this unique effort, more than 400 variables were analysed using a sophisticated AI-based model that now helps public bodies to conduct more precise decision-making, saving them precious time. Successful results achieved during the pilot implementation in 2022 have encouraged us to further develop the model, scaling it to different parts of the world in partnership with more stakeholders. In the end, we must all unite in an effort to save our forests, our common future and our world.

Finally, we would like to express our gratitude to the Turkish Ministry of Agriculture and Forestry for its commitment and exemplary collaboration. We would also like to thank our partners at the World Economic Forum's Artificial Intelligence and Machine Learning platform for their support during the project.

Jeremy Jurgens
Managing Director,
World Economic Forum

The World Economic Forum's Global Risks Report 2023[1] found that failure to mitigate and adapt to climate change, followed by natural disasters and extreme weather events, and biodiversity loss and ecosystem collapse, lead the top 10 risks, ranked by severity, expected to manifest over the next decade. While the threat of wildfires has never been greater than it is today, we are also seeing advances in AI providing applications for pre-, intra- and post-wildfire events. Yet there remain critical barriers to scale and impact that need to be addressed to achieve the full potential of these advances in AI for climate.

As we improve our understanding of the complex impacts of climate change on wildfires, developing and disseminating the knowledge and tools necessary to advance predictions of wildfire risks, informing management decisions that prevent further catastrophic damage to our people and planet, is crucial. There is an urgent need for technological innovation on three fronts: prediction, emergency response and forest management.

The FireAId initiative in collaboration with Koç Holding and Deloitte serves as a space for global climate technology leaders in industry and government to share, learn and accelerate new, sustainable data-driven AI for wildfire efforts. The pilot study and solution approaches laid out in this report show how promising AI interventions can be scaled and replicated in different geographical areas, the enabling role governments can play to align and support these efforts, and avenues for the private sector to engage as part of multistakeholder partnerships that will advance the collective response to this escalating crisis. The findings from this initiative can also be applied to further strengthen efforts in using AI applications to mitigate other climate risks, which can eventually safeguard populations, natural environments and economic prosperity.

During this difficult period of growing fire seasons and climate change, we are committed to continuing and strengthening this global engagement. We hope this report will inspire you to join these efforts, which can address the key drivers of catastrophic fires, increase the pace and scale of forest management and improve the resilience of increasingly threatened communities globally.

Jennifer Steinmann
Global Lead Sustainability & Climate, Deloitte

Living in California, my family and I are keenly aware of wildfires. The increasingly long fire seasons are punctuated by the destruction of nature, infrastructure and property. The human toll is steep: injuries and lives lost among community members and firefighters, evacuations, destroyed homes, dangerous air quality and diverted resources.

Wildfires have long served as natural catalysts for renewal and are integral to healthy forest ecosystems. But climate change is tipping the scales, drying out soils and vegetation, and fuelling more frequent and severe wildfires. Moreover, wildfires are both a cause and an effect of climate change. Burning forests release massive amounts of carbon into the atmosphere, contributing to rising temperatures, and thereby making future wildfires more frequent and severe.

While communities have shown remarkable strength and perseverance in the face of these disasters, more help is needed. Digital technologies hold immense promise in the fight against climate change, and they can help us to both mitigate and adapt to a more fire-prone world. At Deloitte, we are proud to be collaborating with the World Economic Forum and other partners on the FireAId initiative, which aims to improve wildfire prediction and identify the best strategies to extinguish fires through artificial intelligence and machine learning.

This important initiative is one example of the new forms of cooperation needed to tackle the many challenges associated with climate change. Our colleagues at KoçDigital made a promising start in launching this initiative and, together with our alliance partner NVIDIA, we are hard at work to take wildfire risk management to the next level.
It is a daunting task, but together we can make a positive and powerful difference for communities, ecosystems and the climate.

Preface

Advances in the use of AI for fighting wildfires provide an encouraging beginning that can be scaled further with international collaboration.

Kay Firth Butterfield
Head, Artificial Intelligence and Machine Learning, World Economic Forum

Arunima Sarkar
Lead, Artificial Intelligence and Machine Learning, World Economic Forum

Extreme meteorological weather conditions, droughts and floods as a result of the negative effects of climate change have become a global issue all over the world. There is a strong consensus that climate change enhances the likelihood of fires, increases their frequency and severity and extends the periods of wildfire risk. As a result, critical services and resources such as health and safety, forestry, natural disaster and emergency relief agencies, as well as rural planning bodies, are overburdened and the strain on resources is likely to grow. The most vulnerable communities continue to be on the front line, and are often the least resourced to respond to climate impacts.

Early detection of forest fires and the development of effective measures for intervention are needed, together with an increase in preventative measures such as strengthening response capacity by taking advantage of technological developments, fire models, decision tools and global open-source data repositories. While individual initiatives exist, there is a need for a long-term, solution-oriented, coordinated global effort in the fight against forest fires. AI models can help predict which locations are at risk and the best possible strategy to mitigate fire hazards. Building on the other ongoing climate-first efforts across the World Economic Forum, bringing in a holistic approach that focuses on using technology for climate action, FireAId is a concerted effort in data and AI for fighting wildfires.

Türkiye has been grappling with severe wildfires; in response, the Forum initiated the FireAId project with its partner Koç Holding in January 2022. It has since developed this initiative further, with Deloitte joining as a core partner in June 2022. Since then, multiple partners from across the world have come together to contribute their expertise and knowledge and strengthen this initiative. The FireAId project attempts to frame the broader stakeholder conversation regarding AI and wildfires, starting with the first pilot in Türkiye, as well as exploring pathways to scale for similar climate scenarios and discussing other long-term strategies for early detection and prevention of wildfires globally.

In the project's workshops, experts have stressed several points required to increase efforts in this space, with the most agreed-upon being the importance of international cooperation. There is a need for greater collaboration to improve the quality, scope and accessibility of relevant data – which is so critical to the development of AI models for forecasting wildfires – and to enable this with minimum data requirement standards. Encouraging states to share their wildfire data and resources in order to promote the faster development and enhancement of AI technology, and greater cross-government and cross-entity collaboration, is an important prerequisite to addressing barriers in data access and data compatibility. Furthermore, there is a need to augment this with new data sources, beyond historical data, to work towards the real-time applications critical to empowering those facing problems locally. Experts also suggest stepping away from the adversarial framing of "fighting fires" and instead look at ways to "adapt and thrive with fires", meaning "fighting fire with fire" – in other words, using controlled fires that can prevent wildfires, which are unpredictable and much more difficult to contain.

The Forum remains deeply grateful for all the support it has received from partners in helping build this initiative. The findings from the first pilot in Türkiye and the innovative solution approach of Deloitte and other leading partner efforts will be applied to other regions grappling with wildfires to further strengthen their efforts. Responding to this climate crisis requires sustained, long-term efforts that can be achieved only by working together.

Executive summary

FireAId attempts to provide a solution to fighting wildfires, leveraging advances in technology and overcoming existing barriers to scale such efforts.

The rise in occurrence and intensity of wildfires is an unfortunate consequence of climate change. Wildfires are, in themselves, nothing new – they have been a natural phenomenon for millions of years. There has nonetheless been a dramatic increase in both the frequency and severity of wildfires, stoked by climbing average and peak temperatures, prolonged periods of heat and altered rain weather patterns. In the United States alone, the amount of land scorched by wildfire expands unabated. Since 1983, when reliable wildfire tracking data was made available by the National Interagency Fire Center (NIFC), every year an average of 3 million acres of land has gone up in flames. Recalculating that average since 2000, there are now 7 million acres of burned area, a total that has more than doubled in just over 20 years.[2] In South Africa, what once was seasonal has become a more regular phenomenon. The February 2021 wildfire near Cape Town grew to more than 13,000 hectares and spread into the outskirts of the city, engulfing university buildings in the conflagration.[3] In Australia, drier and hotter conditions – eight of the 10 hottest years on record since 2005 – have set the stage for the largest fires in its history, killing or displacing more than 3 billion animals.[4] In Europe, wildfires continue to ravage Mediterranean countries and extend into regions previously not prone to fires. Combined with record heatwaves and drought periods, wildfires endanger finely balanced ecosystems.[5] The trend is expected to continue: the World Meteorological Organization projects a global increase of extreme fires of up to 30% by 2050 and up to 50% by the end of the century.[6]

The damage caused by wildfires can take generations to recover. Worse, the very occurrence of wildfires releases tons of CO_2 into the atmosphere – the 2019–2020 Australian bushfires alone were responsible for more than 400 megatons of carbon dioxide.[7] This, in turn, traps more heat, making further wildfires ever more likely. Without prejudice to the importance of many other climate initiatives, which seek to lower emissions and alleviate environmental pressures in other ways, there can be little doubt that wildfire risk management is itself also a critical component of combating the effects of climate change, as well as protecting habitats, lives and livelihoods around the world.

In fighting fires, every second counts – quick and effective response is critical. More often than not, firefighters must contend with tight budgets and ageing equipment, and reply on experience and gut instinct to plan. Opportunities to modernize exist, but they require investment and effort from specialists who – faced with competing daily priorities – have little incentive to dedicate the necessary resources and talent to develop them. This is where government ministries can make a difference, setting ambitious goals and, crucially, providing funding, to give the issue of wildfire risk management the attention it deserves.

The sheer scale of the task makes it difficult to achieve momentum, demanding both local focus and global coordination. Progress will be iterative and made over the longer term, requiring resolve and public support to see it through. Notable progress has already been made. The availability of relevant data and past studies of wildfire dynamics lay a solid foundation for future work. The aim of this paper is to lower the barriers to that future work by sharing a vision for the solution and describing a project already underway that can serve as inspiration for future developer teams and government officials in what will be and must be a worldwide, coordinated effort.

1 Introduction

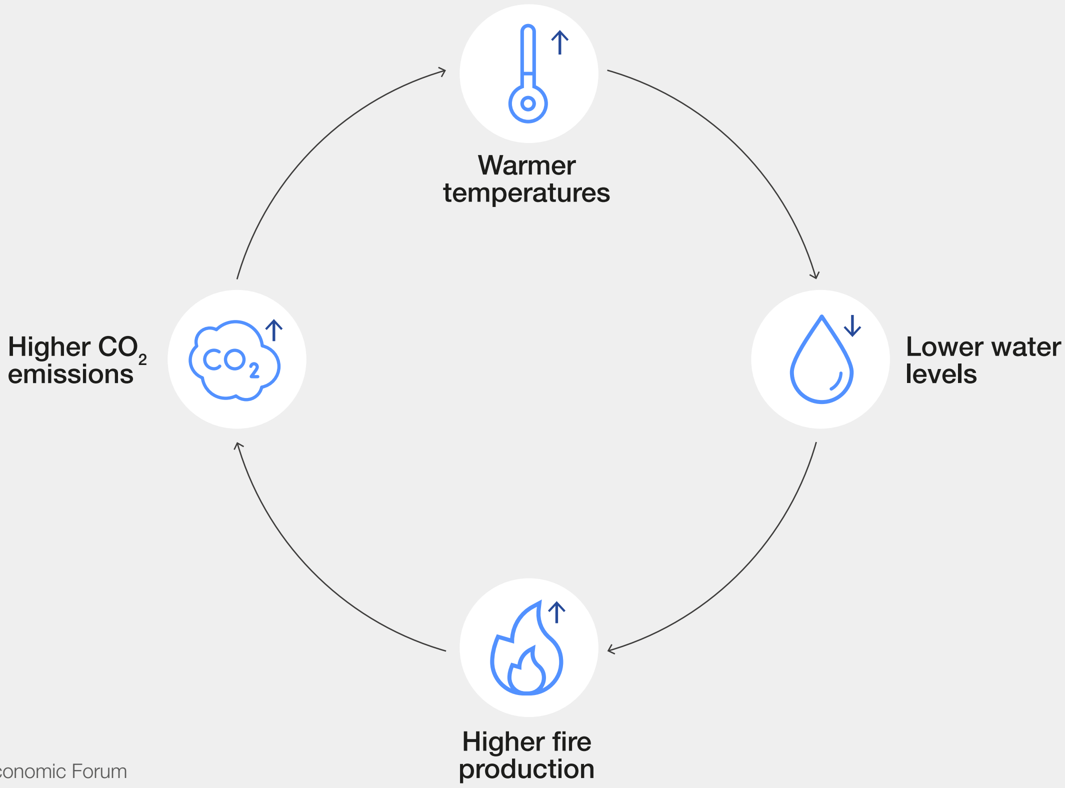
As the threat of wildfires increases, affecting several parts of the world today, technological innovation provides promising solutions.

1.1 The challenge of wildfires

Severity and frequency of wildfires (the problem of wildfires)

A raging wildfire is a fearsome event, destroying and devastating natural resources, lives and livelihoods in its wake. Wildfires are fiendishly difficult to predict. Their frequency and severity increase with every passing year, exacerbated by the effects of global warming and climate change. As temperatures rise, they alter the delicate balance of weather patterns that have – until recently – generally kept wildfires in check. Regular rains and healthy stocks of mountain snow that have preserved ground soil moisture, healthy flora and plentiful water reservoirs are decreasing at an alarming rate during the dry seasons, while hot extremes increase rapidly.[8] The recent extended periods of record summer temperatures have desiccated forests, shrublands and grasslands alike. Although wildfires have long been a natural phenomenon, their increasing frequency along with extreme weather conditions on a global scale have severe consequences that can no longer be regarded as normal.

FIGURE 1 **Global warming causes a positive feedback loop of warmer temperatures, lower water levels, higher fire production and higher CO_2 emissions**



Source: World Economic Forum

Having documented roughly 70,000 wildfires per year since 1983, the United States Environmental Protection Agency (EPA) asserts that the fire seasons with the largest areas burned all occurred within the past 18 years.[9] Similarly, the European Environment Agency (EEA) projects expansion of moderate fire danger zones with burned areas nearly doubling in under 3°C global warming scenarios in EUMED5 countries (southern France, Greece, Italy, Portugal and Spain).[10] Currently, wildfire severity has reached an unprecedented level, with annual average burned areas rising steadily. In the US, there have been approximately 1.5 million wildfire occurrences since 2000, with 237 of these exceeding 100,000 acres burned and 15 exceeding 500,000 acres burned. In comparison to the 1990s, when the annual burned acreage amounted to 3.3 million, the numbers have more than doubled, to 7 million acres burned yearly since 2000.[11] In the past few decades, the world has been experiencing severe effects of climate change and global warming. Recently, the severity and frequency of hot extremes have increased, while cold extremes have decreased. According to the United Nations Environment Programme (UNEP) Cooling and Climate Change fact sheet, 30% of the world's population is exposed to deadly heatwaves on more than 20 days a year. In addition, intensification of heavy precipitation is observed in parallel with a decrease in available water in dry seasons.[12]

7m

Acres burned every year since 2000

More than doubling the annual rate of the 1990s

Projecting these trends suggests that there may be far-reaching consequences for vegetation and soil, as well as a deterioration in air quality and natural ecosystems. Wildfire smoke is an "exceptional event", meaning that the particulate matter to which people and wildlife are exposed is increasingly unregulated. More than 1.5 million people worldwide live in areas where they are routinely exposed to extreme levels of pollution. While prediction mechanisms exist and are improving daily, they often overlook pollution levels and their negative consequences.[13] Forest lands generally provide the majority of freshwater supplies; in the US, this amounts to around 80% of the total. Wildfires severely affect the water quality of rivers, reservoirs and streams – both during a fire and when ashes settle on water surfaces, as well as in subsequent years, when dead landscapes erode more quickly, increasing the accumulation of sediment. The capacity of soil to absorb water and store it usefully becomes compromised, leaving lands more susceptible to flooding. Secondary effects such as diminished reservoir capacities and increased treatment costs put additional pressure on the supply of fresh water.[14] Dead landscapes have fewer nutrients available in their soil, heightening the risk of diseases and delaying the regrowth of diverse flora and fauna. In 2020, wildfires in California alone emitted 91 million tons of carbon dioxide, significant relative to the overall positive contribution of forests acting as the world's "carbon sink" absorbing a net 7.6 billion tons of CO_2 per year.[15]

The severity of wildfires can affect economic and social development. Environmental pollution, property losses and the number of casualties have increased in correlation with wildfires. To remedy this, targeted mitigation strategies must be put in place to understand the scale and severity of previous and future wildfire occurrences.[16] According to projections based on simulation modelling, historical records and current weather trends, fire seasons in the future will have lower fuel moisture and will be greater in length and frequency than those of previous years. Moreover, reburns are likely to take place more frequently due to climate change and have the potential to affect tree regeneration, species composition and the future of the natural environment.[17]

Undeniably, all of the conditions above make forests and forest ecosystems some of the landscapes most vulnerable to climate change due to the drastic increase in the risk of wildfires. There is a life cycle for forests, throughout which wildfire burns can be a perfectly normal feature. Fire is a regular occurrence in Mediterranean forests; in fact, they burn down entirely once every 50 years on average as part of their natural cycle. Were this not to occur, the forest's life cycle would be disturbed, even driving some tree species to extinction. Natural fires purge debris from forest floors, replenishing vital nutrients in the soil, which give plants and animals a new start in life. Without fire, pathways to these nutrients may be obstructed by dead or decaying plants accumulating on the forest floor. The growth of new or smaller plants may also be hindered by this layer of decomposing organic material. Fires are therefore a necessary factor in preserving ecological balance. The issue is not with wildfires themselves, but that they have become both too large and too frequent, failing to create the nourishing ecosystem that many plants and animals need.

1.2 Opportunities to respond to wildfires

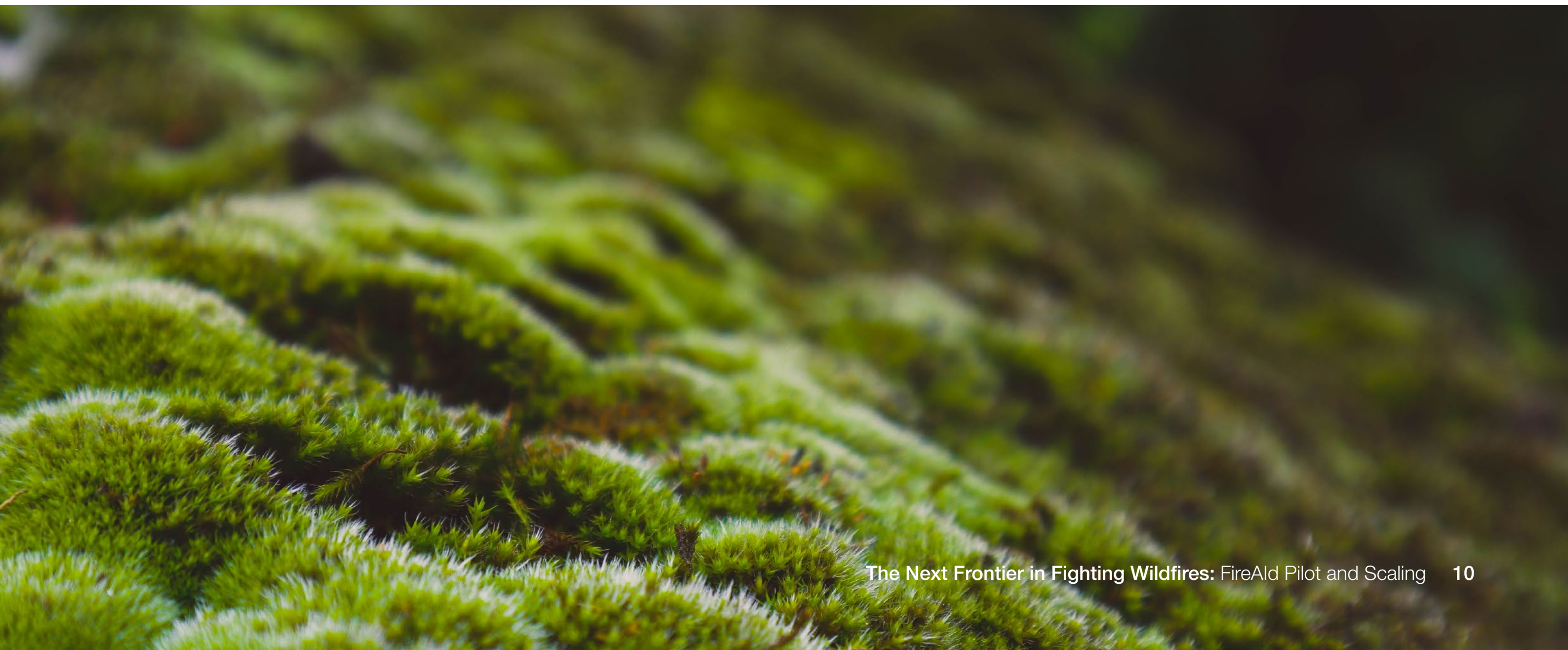
Opportunity that technology provides

This all amounts to a big problem, but not an insurmountable one. Scientists were the first to recognize the gravity of climate change, and have been feverishly studying the topic, its causes and possible strategies to combat it. Volumes of research have been dedicated to understanding wildfires and their relation to climate megatrends. In parallel, analysis technologies such as artificial intelligence (AI) have made tremendous progress – not necessarily with modelling wildfires in mind, but for other use cases, which may – with some clever application – be applied to the wildfire problem.

The dream of autonomous vehicles has driven continuous refinement in computer vision AI, notably in convolutional neural networks (CNN), a specific architecture of deep neural networks (DNN). Such models are "spatially aware" – meaning they consider the context of their surroundings in making predictions. This spatial characteristic is useful to model the advance of the wildfire front line in, potentially, several directions. The beauty of the convolutional kernel is that its first layer allows information extracted from a pixel on an image to account for immediately neighbouring information that might be relevant to that pixel. A simple example of this is a line of light pixels alongside a parallel line of dark pixels, which very likely indicate the edge of some object or geographical feature. Subsequent layers of the neural network evaluate more abstract information derived from the layers preceding it. In the case of facial recognition, the AI starts with pixels, then edges, then eyes, eyebrows and noses, as the algorithm examines data from a larger and larger portion of the image. It is an elegant way to scale the level of information processing from low-level raw pixel values to high-level abstractions, such as features of a person's face, or features of a landscape.

In parallel, to make interactions with computers more human, researchers have experimented with varieties of recurring neural networks (RNN), a different architecture of DNN optimized for sequence prediction. The most recent "transformer" models are behind the marked improvement in natural language processing (NLP), which enables computers to evaluate the meaning in flowing narratives. They also power natural language generation (NLG), a computer's capacity to anticipate the flow of conversation, to deliver human-like chatbot responses or even to write entire essays that readers may struggle to identify as the work of a machine.

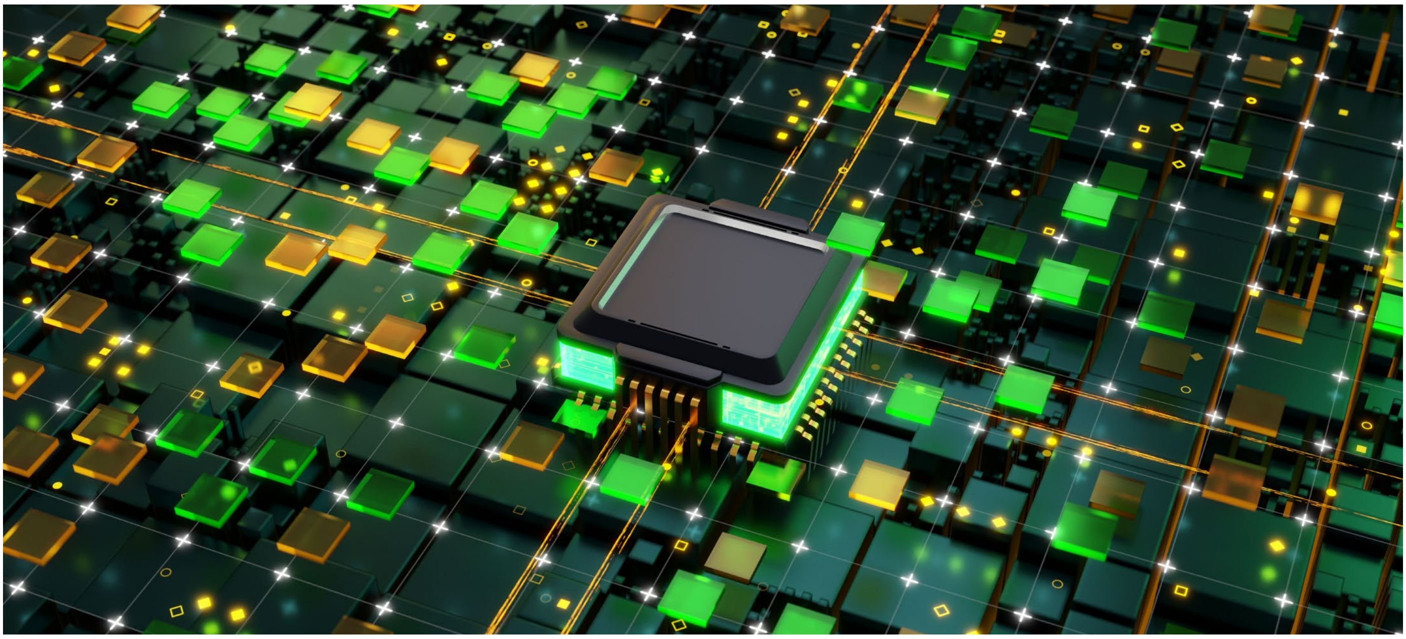
These applications, while unrelated to wildfires, have nonetheless given rise to AI techniques that are highly effective in making predictions for circumstances related to those faced when assessing wildfire risk. It then becomes the creative challenge of the data scientist to envision how these techniques might be used in a different context. This starts with understanding and formulating the new problem in ways that are compatible with existing tools, subject to the availability of sufficient, relevant data.



New advances in artificial intelligence and machine learning

Wider availability of data opens up the possibility of training more complex models. This is important as models with greater predictive power generally require more training data in order to prevent overfitting. This theme is mirrored in the latest scientific publications, where researchers used tabular methods (logistic regression, Random Forests, XGBoost, etc.) to predict the probability of a wildfire outbreak.

One reason why the conceptual approaches of the past have faltered is the non-linear nature of the wildfire problem. For example, one predictive feature for wildfire outbreak is population density. Proximity to urban and suburban areas (indicated by population density) can point to higher fire risk due to human activity – whether fires starting in communities near wooded areas or power lines or as a result of more hikers frequenting natural parks. Population density alone is not a straightforward indicator: the highest densities are in city centres, a rather less flammable landscape of concrete and asphalt and not the origin of wildland fires. Another example, biomass, is a proxy for fuel – the more there is, the greater the potential severity of a wildfire. Yet, if that mass is doused in water, the specific heat capacity of wet fuel (vs. dry fuel) acts as a *barrier* to ignition. Relying on biomass alone would thus often be misleading. Multiple features are required and these individually and even as an ensemble will reveal non-linear relationships with the probability of wildfire outbreak.



“ Wider availability of data opens up the possibility of training more complex models.

Situations such as these are perfect for deep learning, and researchers have creatively exploited this. Some venture beyond deep learning into reinforcement learning, a technique that rose to fame with Google DeepMind's alpha-series of AI models, all trained on games. Unlike deep learning, which relies on curated training data, reinforcement learning is given no labelled data, only an objective, a reward and a training environment filled with rules. Researchers adapted this approach to the problem of wildfire propagation by treating the wildfire as an agent that might choose to move in any direction. The agent was laid over satellite images of historical wildfires, and the reward function was set based on whether it replicated the footprint of the real wildfire or not.

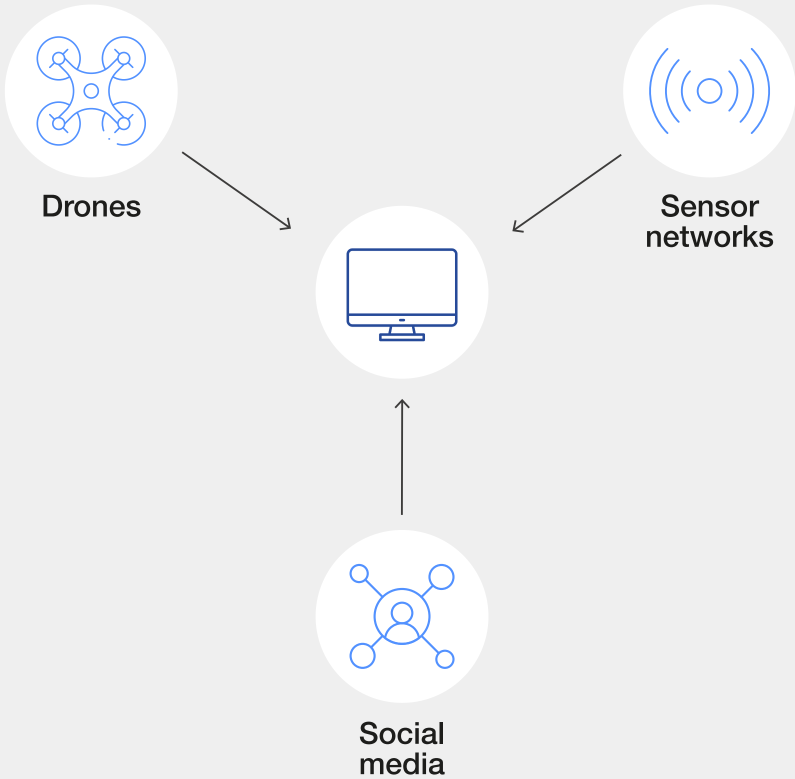
Another way to use deep learning could be adaptation from related fields. Spatiotemporal models used to forecast over a geographic area are largely employed in weather forecasting. With some creative repurposing, this architecture could be very well suited for adaptation to wildfire forecasting. It can consider both temporal and spatial aspects, and its capability in forecasting over a geographic area is already proven.

In tackling the complex problem of wildfire propagation, the methods themselves become computationally complex. That is one strong motivator for attempting to find a better solution using AI, which has already proven successful at finding simpler ways to achieve simpler or even better results in a variety of applications. Google's DeepMind offers some headline-worthy examples, such as predicting how proteins will fold based on their chemical sequence, or beating decades of mathematical work on video-compression algorithms, or finding more efficient methods to perform matrix multiplication. In each of these examples, the AI found heuristic shortcuts by identifying patterns associating a complex array of inputs with known correct outputs in the training sets. All that is needed is a substantial quantity of high-quality representative data.

New data sources (acoustic, drones, smoke detectors, heat sensors)

FIGURE 2

Drones, sensor networks and social media can act as the sensors in a novel network needed to combat wildfires with AI



Source: World Economic Forum

Data sources available today and the means to acquire data are manifold. Due to their ease of manoeuvrability, high spatiotemporal resolution and the fact that pilots are not required, drones are a possible source of timely high-resolution data. In the case of forest fires, unmanned aerial vehicles (UAVs) can provide live images of fire hotspots to firefighters at close range, delivering information on the further course and tendency of the fire. UAVs can do more than passively record images; they can also act, helping to ignite controlled fires through what is known as the "dragon egg system" – suffocating a wildfire by strategically consuming fuel that lies in the wildfire's path by means of a pre-emptive controlled burn.[18] But UAVs can also be helpful in preventing forest fires. Remote pilots have the ability to steer drones through forest areas to collect visual images of potential combustibles that manned aircrafts would not be able to gather. This allows strategies for containment to be developed before forest fires start to develop.[19]

In order to identify wildfires quickly and reliably, sensor networks are used that can detect forest fires within the first hour of ignition, constantly measuring temperature, humidity and air pressure. These sensors can precisely detect different gas ratios in the air, with in-built artificial intelligence being used to reliably raise the alarm in case of fire danger.[20] These next-level smoke detectors can be supplemented with emerging technologies such as embedded systems that rely on audio-based information. These edge-computing implementations are able to pre-process and analyse continuously collected data within milliseconds and effectively identify wildfire sounds over the forest's background soundscape.[21]

Social media and mobile devices provide a huge amount of user-generated content that can be used for wildfire detection and spread information. Using the power of AI, crowds and social media, applications are being created that report wildfires in real time, leveraging images clicked through and uploaded from the smartphones of citizens or mining thousands of tweets related to fire events. Another trend is crowdsourcing wildfire detection. Projects such as ALERTWildfire ask citizens to become firespotters and inspect the network of thousands of cameras being installed by them to help them gain situational awareness of wildfires in their locations.[22]

The opportunity to live and thrive with fire

As the firefighter community readily explains: not all fires are bad; in fact, occasional ‘controlled burns’ are even healthy and necessary.

It is important at this point to state the project objectives more precisely. The aim is less to “fight fires” and more to “enable more effective response to wildfires”. The distinction is important. As the firefighter community readily explains: not all fires are bad; in fact, occasional “controlled burns” are even healthy and necessary. This is because they help prevent or contain the risk of wildfires. “Fighting fire with fire” is a containment strategy: using deliberate fires to consume some of the “fuel” (dry grasses or woodland) in a surgical manner, firefighters create physical “breaks” that slow or entirely prevent the uncontrollable spread of wildfires. Thinning densely wooded forests slow propagation, while burning entire corridors can help restrict wildfires’ ability to advance at all.

Just as the data scientist is armed with modelling tools, the firefighter may choose from a variety of strategies and tactics.

- Smaller streams of water from a firehose, delivered continuously and in a more targeted manner
- Water or the pink fire-retardant Phos-Check dumped from passing aircraft – quick and critical in situations where access is difficult or too dangerous from the ground
- Fire, carefully and deliberately set to rob wildfire of its fuel

While the third “fighting fire with fire” strategy may also be used during wildfires to intercept the onslaught of a wildfire, it is more commonly used as a preventative measure to limit the extent to which a wildfire can spread. However, controlled burns are not guaranteed to succeed. They must be dimensioned appropriately to be effective: “as little as possible, as much as necessary”. It is a balancing act, and one performed on the basis of hard-earned experience in the field. If corridors are too narrow, sparks and hot ash, lifted high into the air from the hellish heat of a wildfire and blown by the wind, could traverse corridors that experience shows would be sufficiently wide to stop the fire progressing. On the flipside, an unnecessarily wide berth would only serve to destroy more habitat, even in a controlled burn manner.

1.3 The current state of wildfire risk management

Substantial effort has been invested over the past 50 years to predict the spread of wildfire

Wildfire risk management is an established field with a spectrum of strategies and techniques. One method of measuring and quantifying fire danger is the Canadian Fire Weather Index (FWI), which has gained some prominence around the world. The FWI consists of six components – three fuel moisture codes and three fire behaviour indices, all based on continuous daily observations of the weather factors, such as temperature, wind speed, relative humidity and 24-hour precipitation. The drying of organic matter enhanced by reduced precipitation and higher temperatures leads to higher Buildup Indexes (BUI), revealing the vulnerability of forests and shrubland and the total amount of fuel available for combustion. The Initial Spread Index (ISI) is based on wind speed and the relative ease of ignition, and estimates the expected rate of fire spread. BUI and ISI collectively form the FWI to quantitatively rate the danger of fires.[23] The fire intensity measured by the FWI has been growing over the past 50 years – since 1980 for southern and eastern Europe, with a 99% confidence level.[24]

Substantial effort has been invested over the past 50 years to predict the *spread* of wildfire. Diligent researchers have tackled the problem mathematically, guiding how best to think about wildfire. First, the problem is split into two components:

1. Predicting whether and where a fire will ignite – the so-called "pre-fire" prediction

2. Predicting in which directions and how quickly the fire will spread – the so-called "post-fire" prediction

These are two very different problems, governed by several factors — some of which are common to both. The first problem – the likelihood of wildfire outbreak – is a function of weather conditions, ground conditions and human activity. The second problem – the prediction of wildfire propagation – depends not only on weather and fuel but also on topography (location of landmarks, incline of the terrain), and less on human activity.

In the research into the problem conducted for this paper, it was discovered that more efforts were focused on the problem of propagation. Mathematical modelling approaches exist and have been put to use programmatically in commercially available tools, notably those stemming from an in-depth study by Richard C. Rothermel for the United States Department of Agriculture (USDA) Forest Service.[25] This seminal paper introduces the concept of modular fuel models, namely what type of material lies in the path of the fire and how combustible it is. The model appeals to data scientists because it relies on recorded weather parameters (data) and focuses on very specific questions, such as density of fuel, how prior burn history affects future probabilities and how to reduce fire hazard. The model is a useful starting point for new approaches, explaining the general dynamics of wildfires and suggesting which inputs are critical for consideration, among them several physical aspects of fuel, weather and topographical inputs. It is also a convenient model, as it requires only the physical and chemical representation of the present fuel, combined with weather conditions, in order to forecast burn. It considers, too, the effects of sparks and burned embers of varying sizes swept up into the air, carried by the wind and falling upon neighbouring trees, shrubs and grassland (more fuel).

Despite the thorough research and profound thought Rothermel invested in the study, the tools that rely on his models struggle to predict accurately, motivating additional research.

- One challenge has been the consideration of multiple trajectories and velocities, where previous models had simplified the problem by considering largely unidirectional propagation.

- Another is the changing combustible nature of fuels in the face of climate change, although Rothermel's work – designed for dead fuels – is perhaps more resilient than other approaches in that sense, as drier climates also desiccate living fuels.

There are several promising ideas about how to address this, among them the notion of unpicking the problem of fire propagation into respective parts, as it is easier to model each independently. One intuitively appealing example stems from the work in 2018[26] of researchers at the Basque Center for Applied Mathematics (BACM), in which the problem of modelling the "fire-front" is split into two parts:

1. A drifting component, driven by the level-set equation – a partial differential equation that can be solved with higher-order finite difference methods that are nonetheless computationally complex

2. A fluctuating component, driven by a multidimensional reaction-diffusion equation (inspired by studies of turbulence), for which Alan Turing had proposed that the presence of diffusion can disrupt the stability of local systems

BOX 1

Examples of a few efforts underway – Google

Google is tracking live fires in order to give fire boundary information to communities and fire authorities. Using geostationary satellites allows for near real-time results with 10–15 minutes between snapshots and results. Google's maps are available in 30 minutes, compared with currently available maps that are of higher accuracy but have a turnaround time of several hours. Google is working to improve both the turnaround time and map precision, and is placing this data on Google maps and sending fire alert notifications to Android users. Google is looking to broaden the work by taking data from NASA's Fire Information for Resource Management (FIRMS)/Moderate Resolution Imaging Spectroradiometer (MODIS) and expanding it to give better insights about wildfires. Building on its boundary-tracking technology, Google is working to improve models for ignition detection and propagation prediction. This technology has enabled the company to be the first to detect fires in remote areas where people are not able to detect the initial signs of wildfires.

BOX 2

Examples of a few efforts underway – NASA

FIRMS makes satellite-derived live fire data available in one minute across the United States using direct broadcast data and new software developed by the University of Wisconsin-Madison's Space Science and Engineering Center (SSEC).[27] Its low-orbit satellites have a latency of less than 60 seconds between Earth observation and wildfire detection. FIRMS was designed by NASA and the US Forest Service to strengthen data availability in the US and Canada to support fire management and provide information to the public. In addition to the live fire data available on the Fire Map, users are able to download data for the past 24 and 48 hours or a week,[28] which includes specific incident information, situation reports, fire perimeters, fire danger ratings and more.

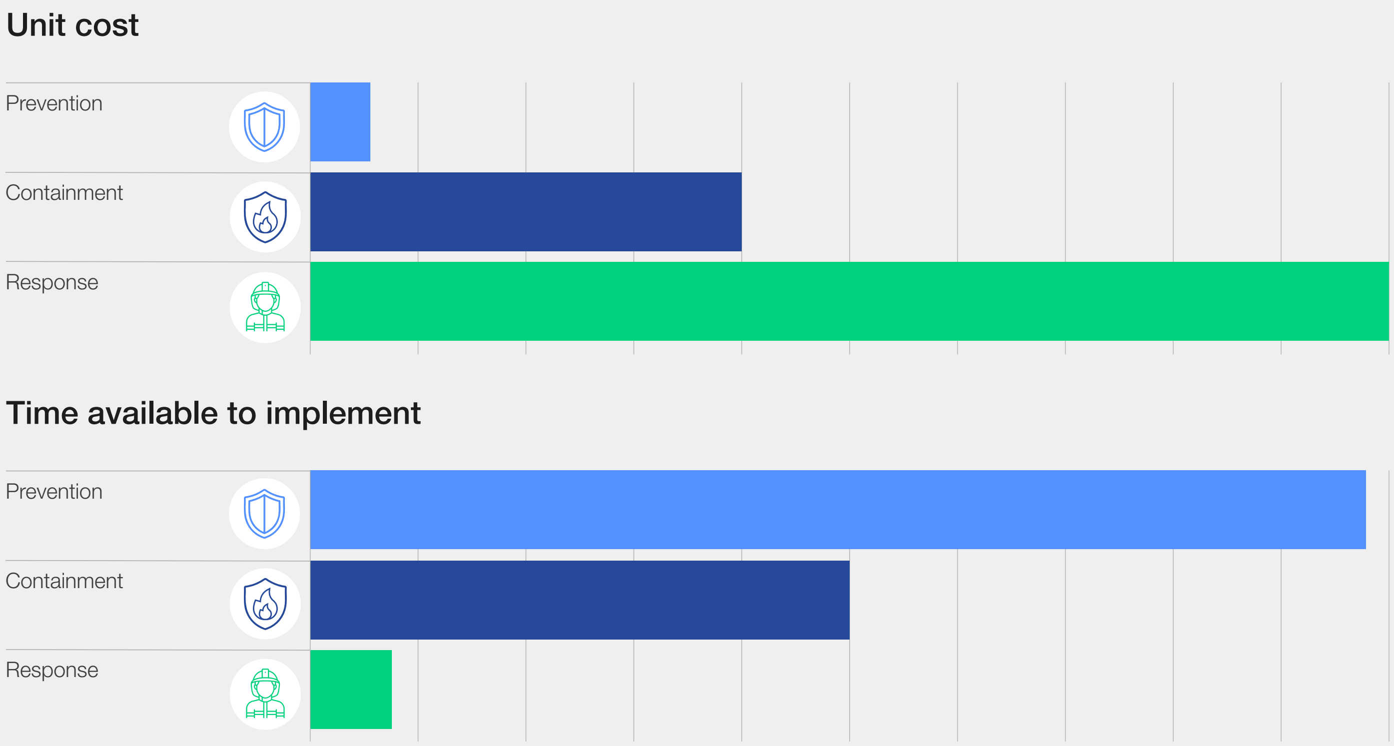
2 Desired impact – an overarching vision

What does a world in which AI systems for wildfires are optimized look like?

2.1 Wildfire risk-management strategies

Wildfire risk management can employ a variety of tactics – each accompanied by a unique set of challenges. These tactics fall generally under three strategies: prevention, containment and response.

FIGURE 3 Wildfire risk-management strategies



Source: Deloitte

Measures intended to **prevent** the outbreak of wildfires are important, but difficult to enforce. They rely on cooperation from municipalities and individuals. Municipalities dictate and enforce local laws, making the public aware of heightened fire risk and the penalties individuals face for reckless behaviour. Most of the population heeds the warnings. Nevertheless, there are always those who are either oblivious or over-confident, underestimating the dangers of their actions. Warnings and fines are important, but are – without enforcement –a passive measure, unlikely to influence the reckless. Yet there are simply not sufficient resources to patrol all at-risk areas. Rangers need help. Having sensors at select locations within a forest and using satellite or drone footage and crowdsourced intelligence are all viable components, yet they may distract and confuse if taken in their "raw" format. To be truly helpful, rangers need the data to be transformed into usable information – and not by armies of back-office staff performing deep analysis and producing monthly reports. Even the best information delivered too late will not improve anything: it must be updated frequently, holistic, focused and easily understandable.

Planned **containment** will not halt the outbreak of fires, but it limits the damage they can cause. Such measures rest more squarely in the hands of firefighters and forestry professionals. Yet even the relative calm of this preventative maintenance can be deceptive. Numerous questions arise: Where to prune the forest? What to prioritize? How much to prune – how wide, how long a corridor? How much confidence can there be that these measures will be effective, or that the preventative burn can truly be controlled? Could environmental conditions change such that those involved might inadvertently start an uncontrolled wildfire? Forestry and firefighting professionals need planning tools that take more than just gut feelings and experience into account. The firefighting community concedes that evolving environmental conditions have made fires increasingly difficult to predict and control – whether in preventative maintenance or combating wildfires. In a fast-changing world, planners need a more comprehensive view, as well as the ability to thoroughly evaluate the efficacy of potentially costly options.

The last strategic option, **response**, is the defensive one. A wildfire has broken out and must be stopped. There is not a moment to lose. The fire advances, seemingly in all directions, or most quickly in one direction driven by prevailing winds. Access is limited and dangerous. Water is scarce. Reports of property damage and lives lost stream across television screens reporting the drama. One wrong move can make the difference between relief and disaster, between life and death. Response must be properly designed and executed swiftly to be effective. Yet, in the heat of the moment, there can be no calm in which to contemplate the possible alternatives. Firefighters are confronted with the same challenges of planned maintenance – compressed into high-intensity time spans measured in minutes, not hours. Today, it often comes down to using tried and true approaches from past experience. Often, these will suffice, even if they may not always be the optimal approach – but “good” implemented on time beats “perfect” too late.

A solution for the short term

For the short term, a reasonably accurate prediction engine that takes both short- and long-term trends into account is being sought.

For the short term, a reasonably accurate prediction engine that takes both short- and long-term trends into account is being sought, one that can identify patterns of concern across a wide set of inputs and can thereby provide a useful representation of a fire-stricken environment to test multiple intervention measures. A solution such as this takes many forms – a data consolidation, a prediction engine and a simulation platform – each playing a vital role, each interconnected.

Stage 1: Defining the problem in exact terms as well as the solution requirements is the essential first step. Targets must be clearly defined – what exactly is being predicted, oriented around the three major firefighting strategies: prevent, contain and respond.

Stage 2: Data consolidation means connecting a network of inputs – from sensors on the ground to satellites in orbit – into a useful body of data that provides a more holistic view. Just as the brain relies on the eyes, ears and nose to perceive its environment, so an AI must rely on multiple sensory inputs. And just as the brain compares current perceptions to past experiences, so an AI must rely on a database of situations in order to identify common patterns and benefit from the hindsight afforded by past experience. Creating a rich data landscape is the critical second step – as there can be no AI without data. The question of which inputs constitute that data is driven by what is required – the definition of the problem to be solved in the first step.

Stage 3: Armed with relevant data of reasonable quality and in sufficient quantity, attention turns to the pivotal third step, turning that data into useful information, most importantly into predictions. The same prediction capabilities may support one or more of these strategies. Predicting an outbreak – where a wildfire is likely to start – is a cornerstone of any of the three strategies. Predicting propagation – the trajectory and speed of a wildfire once started – is useful to containment planning as well as to the active response in the moment. Predicting the effect of measures – the use of water or controlled burns – offers heightened appreciation of the effectiveness of response strategies.

Stage 4: These three stages of solution design culminate in the fourth and – for now – final step. Having designed a forecasting engine that provides reasonable accuracy and precision based purely on factual inputs – topographical, meteorological, behavioural – one last, critical feature is introduced: simulation. The ability of this system not just to provide a forecast but also to observe the effects of interventions vs. baseline “do nothing” outcomes will amount to a quantum leap in combating wildfires. Some companies, such as NVIDIA, have set themselves the ambitious goal of modelling weather patterns and their effects on a global scale. The aspirational Earth 2 project uses the simulation Omniverse to build a digital twin of the Earth that enables scientists to study sensitivities in often volatile assumptions, or in tipping-point situations, where historical data may no longer reliably reflect what is to come. For the purposes of wildfire risk management, the narrower, more focused goal is set of predicting how intervention measures can alter the course of wildfire propagation.

The long-term vision

Stage 5: Responding to wildfires is a battle against the clock. Eliminating delays between perceiving a problem and taking action would concentrate efforts on a smaller area that could be brought more quickly under control. Longer term, this could take the shape of a semi-autonomous AI-controlled fire defence system. Such a system would supplement the current scope, adding actuation planning atop forecasting. It would also add to the significance of the digital twin: actuators would be added to and tested in the simulation environment. In addition to informing humans on most effective strategies, the simulation environment would train the separate AI models in controlling new equipment. With regard to operations, the AI-controlled fire defence system would itself translate forecasts and simulated outcomes into preventative or responsive measures that its network of remote-controlled devices could take. Autonomous systems such as these are a distant prospect for many reasons, the first of which is that they must be robust and reliable, so as not to present more of a problem than a solution. They must also operate in a transparent manner, understandable to their human creators, who must retain the option to intervene themselves if the system performs abnormally. Autonomous systems will not someday magically appear. They will be possible only if incremental steps are taken in that direction – crucially, in refining the predictive power of the data on which the AIs are so dependent.

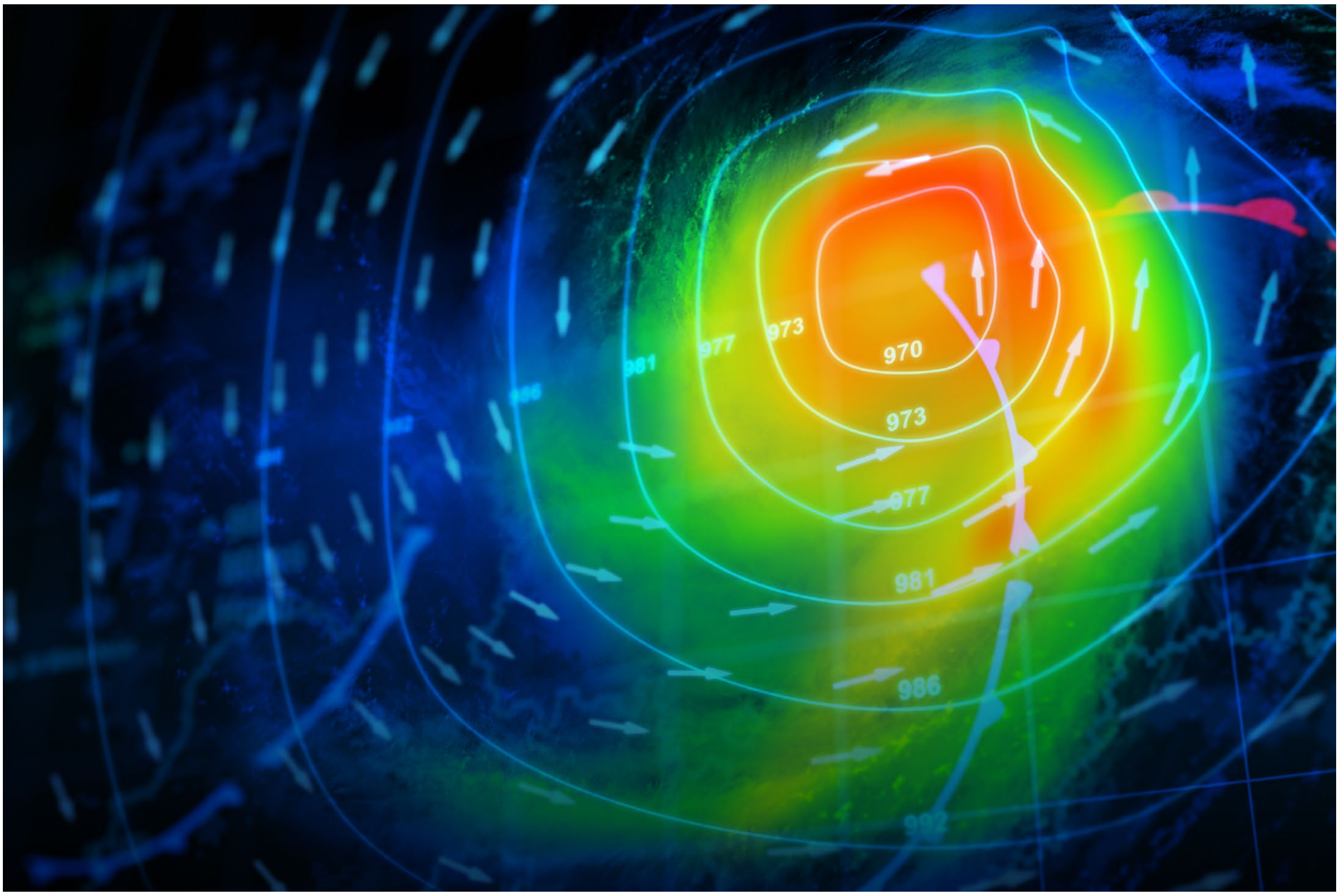
TABLE 1 **Five stages of a wildfire risk-management solution**

	Stage 1 Definition	Stage 2 Data	Stage 3 Modelling	Stage 4 Digital twin	Stage 5 Automation
Activity	Clarify goals and end-user expectations	Connect network of inputs	Mathematically define the problem	Visualization, interaction, simulation	Identify opportunities for automation
		Consolidating data sources			Technology (hardware) needs
		Evaluate on relevance, representativeness, quality			Specify trustworthy AI considerations
Outcomes	Concrete requirements	Rich data landscape	Prediction objectives: outbreak and propagation	Inform real-world decisions	Autonomous wildfire risk management

Source: Deloitte

The Fourth Industrial Revolution technology interplay accelerating the potential

The clever application of various technologies – notably, but not exclusively AI – can be a game changer. Long term, a future network of AI-controlled wildfire sentinels, drones and sensors working seamlessly together to continuously monitor and even intervene with timely, surgical precision can be envisioned. However, an aspirational future such as this is still a long way off. The world cannot afford to wait – and it need not. Widely available technologies already exist today, as seen from the examples earlier that can dramatically improve firefighting capabilities in monitoring, planning and execution.



2.2 About FireAId: using AI for wildfire prediction and prevention

> FireAId – a new initiative from the Forum on AI for wildfire prediction and prevention – aims to facilitate the application of AI to help combat wildfires.

The potential of AI, machine learning (ML) and other recent developments in advanced technologies to tackle a major global issue such as wildfires is immense, yet this potential is far from being reached. To this end, the World Economic Forum's Artificial Intelligence and Machine Learning platform is scaling up efforts to proactively engage stakeholders to channel AI and ML innovations towards wildfire prediction and prevention.

FireAId – a new initiative from the Forum on AI for wildfire prediction and prevention – aims to facilitate the application of AI to help combat wildfires. As the average annual global cost of wildfires is about $50 billion,[29] this initiative builds on the global need to improve the efficiency and cost-effectiveness of wildfire efforts. It adopts a multistakeholder approach that brings together expertise from technology companies, government, civil society and international organizations to collaborate and unlock the broader barriers to responsible deployment of AI systems for wildfire prediction and prevention.

The Forum launched the FireAId[30] initiative in January 2022 with Koç Holding as a starting point, with the aim of developing a more concerted and cooperative effort to apply AI systems to wildfire prediction and prevention. This initiative serves as a global node and facilitator for a network of providers and users of data and AI solutions for wildfires. The initiative aims to advance curated AI efforts, partnership-building and government-capacity development to fast-track the development of new AI solutions addressing this existential issue. The effort will be organized and delivered in cooperation with partner institutions, including leading international organizations.

Koç Holding conducted the first FireAId pilot in Türkiye by offering KoçDigital's unique AI capabilities to public institutions, such as the Turkish Ministry of Agriculture and Forestry (TMAF). Through this collaboration, an AI-driven interactive wildfire risk map has been created that models for wildfire probability and severity, contributing to optimal resource allocation. By aggregating lessons from this effort, Koç Holding has taken a leading role in the creation of this report.

Since joining the FireAId initiative in June 2022, Deloitte has been a vital contributor to the Forum's AI for wildfire prediction and prevention journey, strengthening the wildfire management community learnings from its own AI for wildfire prediction efforts.

3 'An encouraging start'

Two promising approaches to wildfire management, from Deloitte and KoçDigital, are outlined below.

3.1 Deloitte wildfire-management solution approach

The cornerstone of the solution concept focuses on predicting the *outbreak* of wildfires by making use of satellite imagery and weather data. A common misconception is that wildfires are a "weather problem" stoked by global warming – presuming an examination of weather data alone will suffice.

Wildfires are not purely a "weather problem" but are equally governed by geography and human activity. Geographic considerations extend beyond the elimination of low-/no-risk zones such as barren mountaintops and lakes. Instead, fine differentiations in terrain and in the "fuel" (combustible vegetation) are the leading geographic factors: forests, shrubs and grasslands will have substantially different burn characteristics, as will differing types of forest wood or grasses. The density of foliage matters and ground moisture can greatly alter the ignitable conditions – meteorological metrics on air humidity do not suffice. Data delivered in near-real time is of tantamount importance, yet the data need not all be time-series data. Static geographical data – topography and landmarks such as power lines, hiking paths and campsites – also have predictive power, albeit more for the second forecasting objective: the spread of wildfires that have already ignited.

> Wildfires are not purely a 'weather problem' but are equally governed by geography and human activity.

It is of critical importance to firefighters how the fires could *evolve* after having started, how the "fire-front" might advance. For this forecasting tool to be truly useful, it must predict not only the *outbreak* of wildfires, but their likely trajectories – and, as has been shown, the speed of *propagation*. However, ultimately the aim is to advise on the best response. One option considered was a recommender system that serves up the past experience most relevant to current situations. A digital twin would be a more powerful option still – and within reach, given the technology partnership between Deloitte and NVIDIA. Where Earth 2[31] creates a higher-level virtual reality at planetary scale to supercharge scientific study, the wildfire use case opts for a smaller, more detailed scope: a simulation environment that combines AI with the physics of fire and its interaction with water, encoded into NVIDIA's Modulus SDK.

The digital twin presents firefighters with the possibility of testing hypotheses of intervention measures and observing their outcomes in time-accelerated simulations of the region under their care. Sophisticated simulations rather than back-of-the-envelope calculations and gut feelings complement their professional judgement. This last "scenarios" component is as ambitious as "outbreak" and "propagation", adding the missing component to help firefighters optimize management of precious resources, primarily the safety of their firefighting crews.

Performance metrics

Vital to any prediction goal is the appropriate success metric. Wildfires remain a relatively rare, albeit dramatic, event. Plotting the outbreak of wildfires beside "non-events" in similar environmental conditions produces a non-normal distribution with a large skew. In such cases, optimization metrics such as "accuracy" are misleading: the distribution can be "accurately" approximated by incidence probability y=0, without AI or modelling of any kind. While predicting correctly on average, it also fails to find a single anomaly. The solution is to optimize to a more suitable metric to skewed distributions, such as the F1 score, the harmonic average between *precision* and *recall*. *Precision* seeks to identify the portion of "true positives" (predicted wildfires that actually turn out to be wildfires) over "all positives" (all *predictions* of wildfire, regardless of whether right or wrong). By contrast, *recall* seeks to identify the portion of "true positives" relative to "all positives the model should have predicted" (*correctly predicted* wildfires and actual wildfires the model had *failed to predict*).

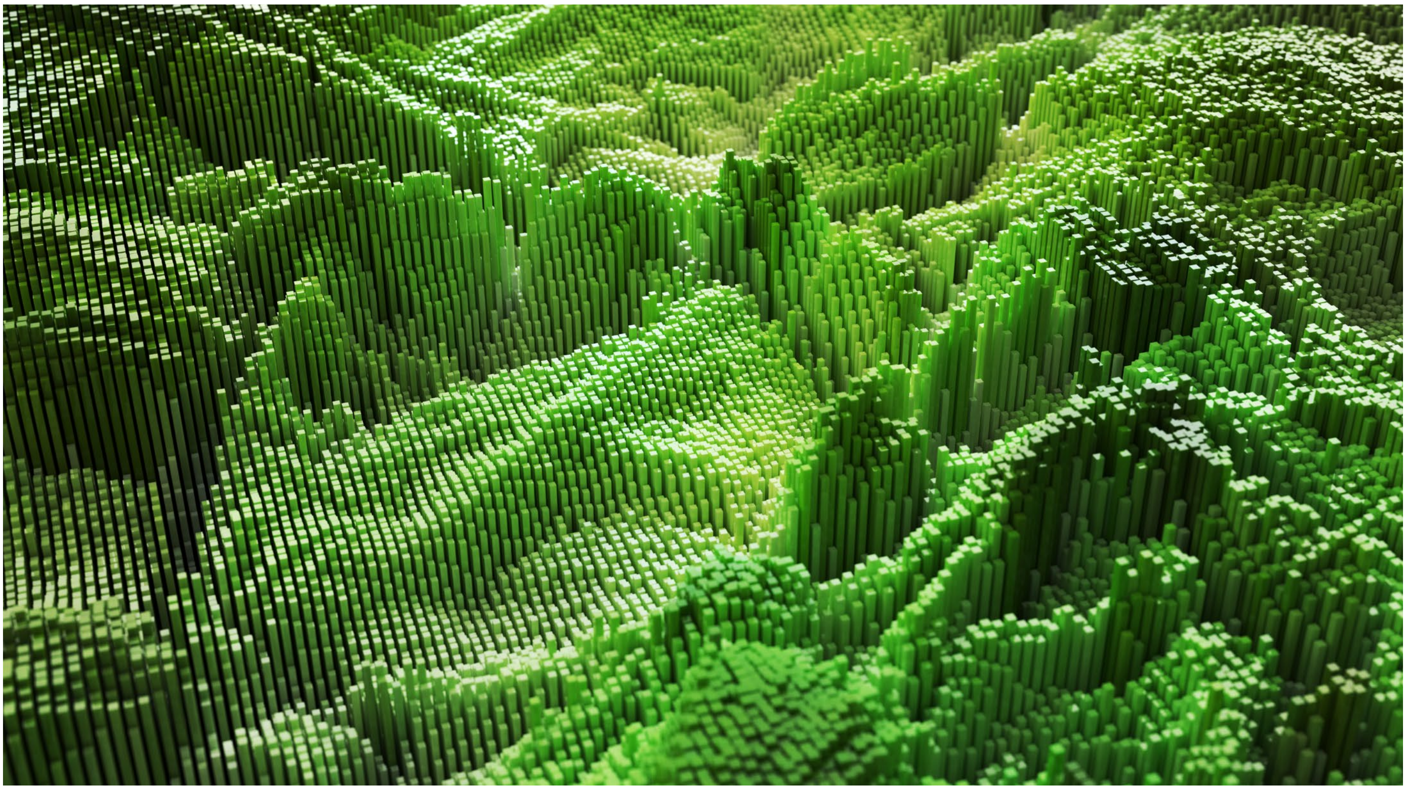
Data exploration

With the concept largely defined, the data exploration and research examines quantity, quality and suitability of available data, as well as identifying multicollinearity (a statistically strong correlation between independent variables) and feature relevance to the prediction goals, resulting in a combination of dynamic (weather) and static (topographical) data.

Topographical data contains valuable information on terrain, altitudes, inclines and the location of high-risk infrastructure such as power lines and campsites. While topography and infrastructure can change over time, the intervals are long and the data can be considered static, which simplifies data acquisition. It is significantly more challenging to build a robust data pipeline for dynamic data.

For one thing, dynamic data sources have different shapes – breadth of features, granularities, regularity of updates – which necessitate a correspondingly flexible structure to the data repository. Second, data volumes become difficult to manage; one of the data sources updates several times per day. Satellite imagery proved too bulky and infrequent for use beyond static terrain data to provide the near-real-time information firefighters need. (Between them, images from European Space Agency [ESA] satellites Sentinel-1 and Sentinel-2 are updated every five days.) While the images are freely available, they can only practically be accessed through application programming interfaces (APIs), which – at the geographic scale under consideration – would become prohibitively expensive to source, process and store.

“ Forecasting wildfires requires models that can accommodate both a geospatial and a temporal context.



AI modelling approaches

Forecasting wildfires requires models that can accommodate both a geospatial and a temporal context. In other words, what happens at one point on the map can influence the neighbouring points, and what happened in the last time frame will affect the next.

Computer vision AI is built on convolutional neural networks (CNNs), a variant of deep neural networks (DNNs) optimized for the spatial context. In the field of time-series forecasting, by contrast, AI approaches are dominated by recurring neural networks (RNNs). Remarkable advances in the time-series forecasting of natural language understanding through the “transformer” algorithm are promising, but no one algorithm reigns supreme. Rather, the optimal approach depends on characteristics of the historical data.

Neither CNNs nor RNNs alone fully address the needs of wildfire forecasting. While RNNs may predict a possible conclusion to a sentence, this represents a one-dimensional prediction. And although CNNs are equipped to make predictions that take the carryover effects of neighbouring coordinates into account, this is a snapshot prediction.

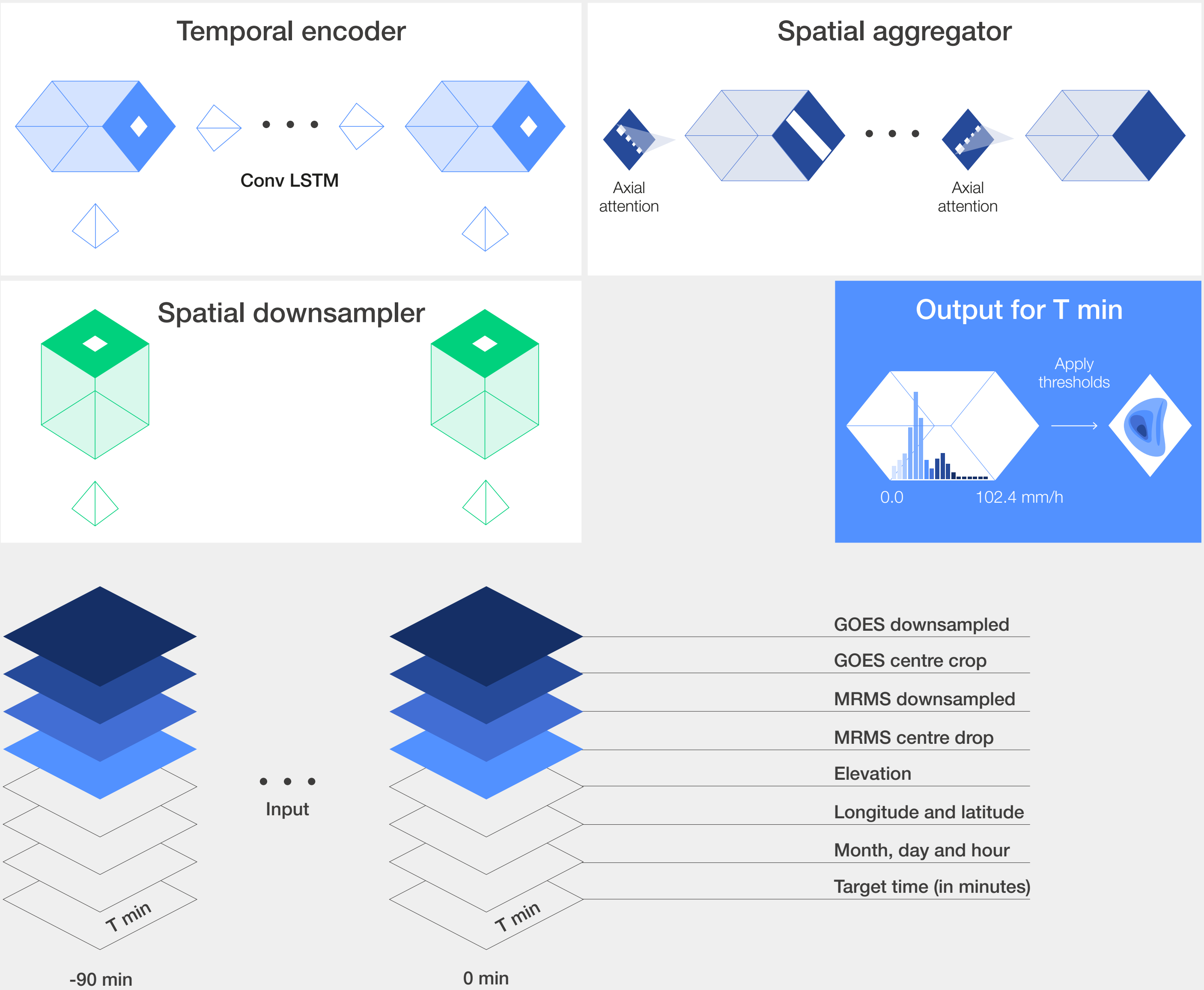
Researchers at Google published MetNet, a deep learning architecture consisting of a CNN nested inside an RNN (CNN-LSTM) designed to forecast precipitation.[32] They enhanced their long short-term memory (LSTM) algorithm with an element inspired by the transformer called axial attention, which allows pixels to "pay attention" to each other across the geographic space; this further improves contextual awareness.

In parallel, NVIDIA's geospatial and machine-learning solution architect implemented FourCastNet[33] by training on the 36 years of ERA5 (weather data from the European Centre for Medium-Range Weather Forecasts [ECMWF]) to predict weather dynamics up to 10 days into the future. Both models are promising and worthy contenders for producing a next-generation, more precise wildfire prediction solution.

Deloitte's baseline model: MetNet using the NOAA dataset

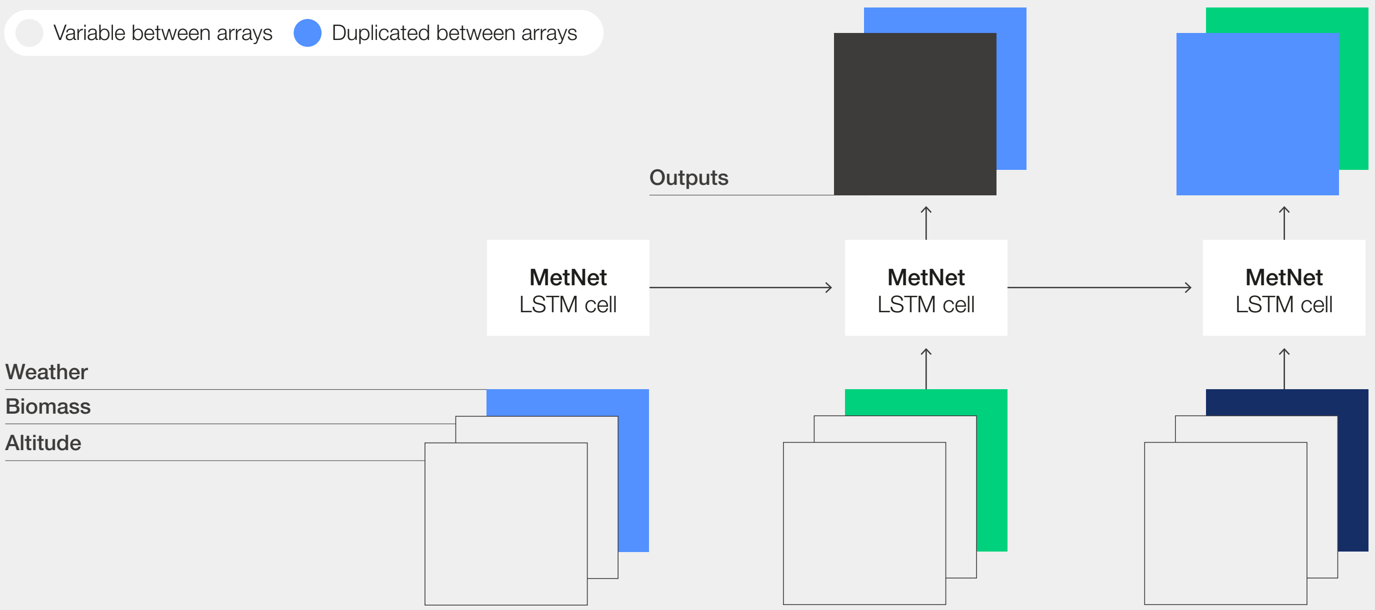
Deloitte's baseline model is MetNet using the National Oceanographic and Atmospheric Administration (NOAA) dataset to focus on prediction with the most current information on the immediate forecasting horizon, a "nowcasting" problem. A second AFNO-Model (Adaptive Fourier Neural Operator), as used for the windstorm predicting FourCastNet, then picks up where the modified MetNet leaves off, tasked with a slightly longer forecasting period. It also serves as a benchmark or challenger model to the MetNet implementation.

FIGURE 4 **Google's MetNet architecture**



Source: Sønder, C. K. et al., 30 March 2020. "MetNet: A Neutral Weather Model for Precipitation Forecasting", Google Research: https://arxiv.org/pdf/2003.12140.pdf

FIGURE 5 | **Deloitte's adaptation of the MetNet architecture implementation (simplification)**



Source: Deloitte

Deloitte's adaptation of the weather models is well illustrated by modifications made to MetNet. The original architecture considers a geographical input space (collection of input features) with dimensions four times the size of the output space (collection of predictions). The philosophy behind this was that their input space could consider all of the air/features that could pass over their output space within their forecasting window, thus giving context. Application to wildfires shrinks the size of the input space (geographic area used for training) to the same dimensions as the output space (geographic area for prediction). Shrinking dimensionality is a pragmatic measure intended to improve computational efficiency. This circumvents the requirement for time-of-forecast context by instead using weather *forecasting* data (as opposed to only reported *actual* weather conditions), and directly overlaying the weather features at the time of inference.

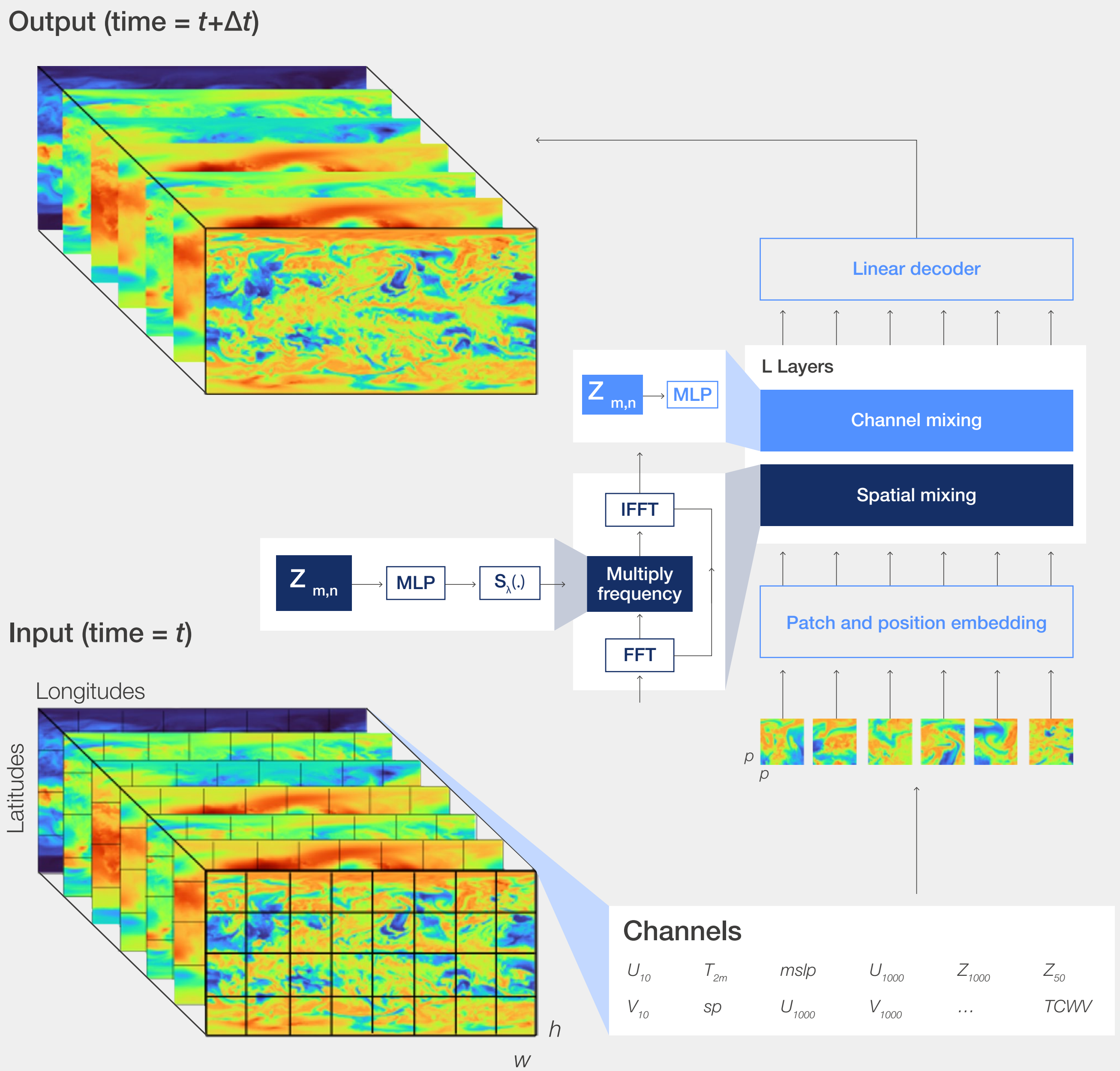
The modification applies the RNN over historical timesteps and includes a "forecast time" input layer. This input layer instructs the model on how far in the future to predict for the RNN cell after the present timestep. The architecture applies the RNN over future timesteps and uploads time-dependent features at the timestep for which they were forecasted. Deloitte's modified MetNet is trained on the most dynamic weather data, from NOAA, in which both the actual observed weather conditions *and* the forecasts are updated several times a day. NOAA's strengths lie in its update frequency, but also in the inclusion of historized forecasts, as the model can also compare later actuals with prior predictions, learning from that association.

The FourCastNet (FCN), by contrast, is based on a multilayer transformer network with an adaptive Fourier neural operator (AFNO). It implements a continuous global convolution in the Fourier domain to mix the tokens with reduced complexity.[34] The block-wise channel mixing uses MLP, while the spatial token mixing uses soft-thresholding. FCN makes use of the richer palette of features available from ERA5 data, weaving together 20 ERA5 variables with the AFNO model contained within the NVIDIA Modulus SDK. Rigorous out-of-sample testing, comparing predictions to later years of ERA5 (2018) and using both root-mean-squared-error (RMSE) and a latitude-weighted anomaly correlation coefficient (ACC) demonstrated a high degree of fidelity to the original academic work.[35]

This architecture provides more flexibility, scalability and a faster computational speed, allowing the use of large ensemble forecasting and a high resolution. FCN generates global data-driven forecasts at a 0.25° latitude-longitude resolution, capturing features at small scales, which can make the difference in predicting generally anomalous events such as wildfires. Importantly, its use of ensembles limits the uncertainties in forecasting extreme weather events and provides greater reliability, especially in long-term predictions.[36]

Both models require modification to their input and output layers. In its base configuration, FCN predicts changing variables relevant to an extreme weather event: for example, wind speed to forecast hurricanes. To forecast wildfires instead, weather models must be adapted to predict the probability of ignition, which takes into account weather, terrain and other features related to fire outbreaks.

FIGURE 6 **FourCastNet an adaptive Fourier neural operator architecture**



Source: Pathak, J. et al., "FourCastNet: A Global Data-Driven High-Resolution Weather Model Using Adaptive Fourier Neural Operators": https://arxiv.org/pdf/2202.11214.pdf

Beyond the architecture of the model, two major questions arise from a machine learning operations (MLOps) perspective.

- The first and obvious question is: are the features used for prediction available at inference time? Otherwise, how is it possible to predict in a timely manner? The NOAA dataset fulfils this criterion, with both actuals and forecasts uploaded only hours after forecasts are generated – available the same day.
- The second, more subtle, question centres on the robustness of the model: how similar is the training data to the data experienced in operation? This consideration pertains both to at the time of training (representativeness) as well as over time (drift). For samples taken at the same point in time, variance in pre-processing could introduce a skew or bias between training and operational data. Representativeness of samples that were demonstrably valid at training could erode over time as the world moves on and the model is not retrained to keep up. The systematic divergence forming between the distribution of input data experienced in the training vs. the inference phase is the MLOps notion of "data drift". Both types of skew are potential causes of performance degradation that can creep into models without rigorous monitoring.

The modified MetNet model makes use of weather *forecasts* to serve predictions that address the risk of variance in pre-processing regarding weather training data. Most weather data sources store only actual historical values rather than their forecasts. Errors in that forecast data (vs. the later actual conditions) could produce a source of skew as the model learns from real historical weather values. The model learns to account for weather-forecasting error by incorporating historized NOAA forecasts.

Climate change will affect the distribution of weather data over time, introducing risk of drifting data distributions. As average temperatures increase, biomass distributions will also evolve. The behaviour of wildfires will also change, becoming more frequent, more intense, larger and faster to spread. The predictive power of any ML model is jeopardized when trained on data that no longer fairly represents what it will encounter in operation. The same holds true for any model that attempts to predict based on how wildfires "used to behave". A regime of monitoring and retraining at regular intervals will be a critical component of any well-performing prediction model.

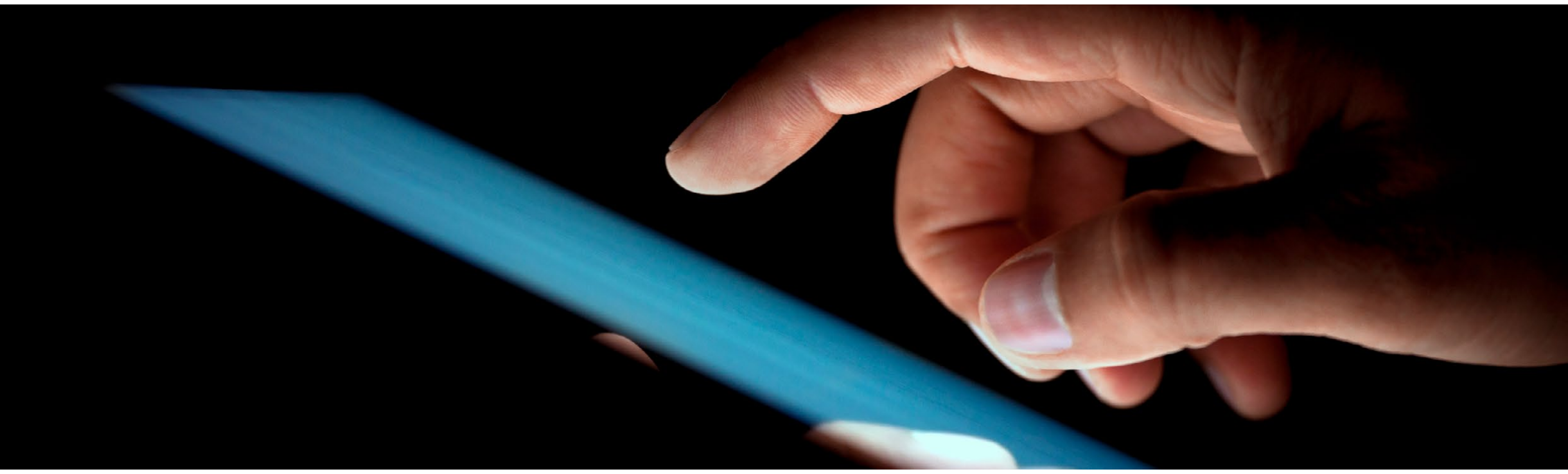
The advanced "outbreak" forecasting model is only one piece of the puzzle. Additional factors are required to achieve the second objective: the prediction of an existing wildfire's "propagation". The simplification that topographical data be considered static is perfectly valid for the purposes of the data pipeline, but not for modelling. The firefighter community emphasized that prior burn history correlates with propensity to burn again in the future, altering the condition of the soil and vegetation – the "fuel". In other words, at least one topographical feature is indeed dynamic. Another weather dataset, ERA5, is updated only once every four to six weeks, making it unsuitable for the nowcasting function, but still useful for identifying long-term trends. Its history dates back to 1950, and it has a rich set of descriptive features. The long history and wide range of variables make it well suited to capturing the dynamic of *prior* burn history of a region – a factor relevant to the fuel component of the topographical AI model. There are additional approaches to quantifying burn history and calculating its effect on fire. APIs with historic fire data are available; these allow the model to consider how much time has passed since the area last burned, thus implying how much fuel is present.

“ The advanced ‘outbreak’ forecasting model is only one piece of the puzzle. Additional factors are required to achieve the second objective: the prediction of an existing wildfire's ‘propagation’.

User interface

The firefighter community made the importance of an intuitive user interface abundantly clear. The centrepiece of the interface is a dynamic map, which users can easily pan and zoom to navigate to what they want to see. The map is flanked by a set of controls and key statistics, which dynamically update depending on the focus. The default displays the averages for the entire region shown on the map. Once the user clicks on a location, the statistics update to reflect conditions at that specific location. Similarly, if the user zooms into a section of the map, the statistics update to reflect the new average of the visible range. A timeline depicts the point in time of the prediction within the forecast horizon. The user invokes simulations by switching to "scenario" mode, where the success of various intervention measures may be tested against given environmental conditions. Modifying the environmental conditions is a form of sensitivity analysis, by which the user may gain confidence in the chances of success for any particular measure.

While much has been accomplished, both the forecasting models and the scenario engine are works in progress, each influencing the other. The ambitious goals in terms of functionality, reliability and user operability require time, focus and input from a wide range of experts. Rigorous testing follows each iterative update to the forecasting model, which is then passed on to the scenario engine and connected to the user front-end at regular intervals when the team feels the overall testing is worth the effort of integrating that components.



3.2 KoçDigital Türkiye pilot

As the Turkish Ministry of Agriculture and Forestry, we have been working on protecting, extending and expanding our forest and forest resources and sustainably managing our ecosystem to create social benefits. Like other countries, Türkiye has been striving against wildfires originating from extreme meteorological conditions, drought and climate change. Geographically, Türkiye has a Mediterranean climate, which makes most of our forests prone to wildfires – 60% of our forests are in first and second-degree fire-prone areas. For this reason, wildfires are among our priorities.

Bekir Karacabey, Turkish Ministry of Agriculture and Forestry, General Manager

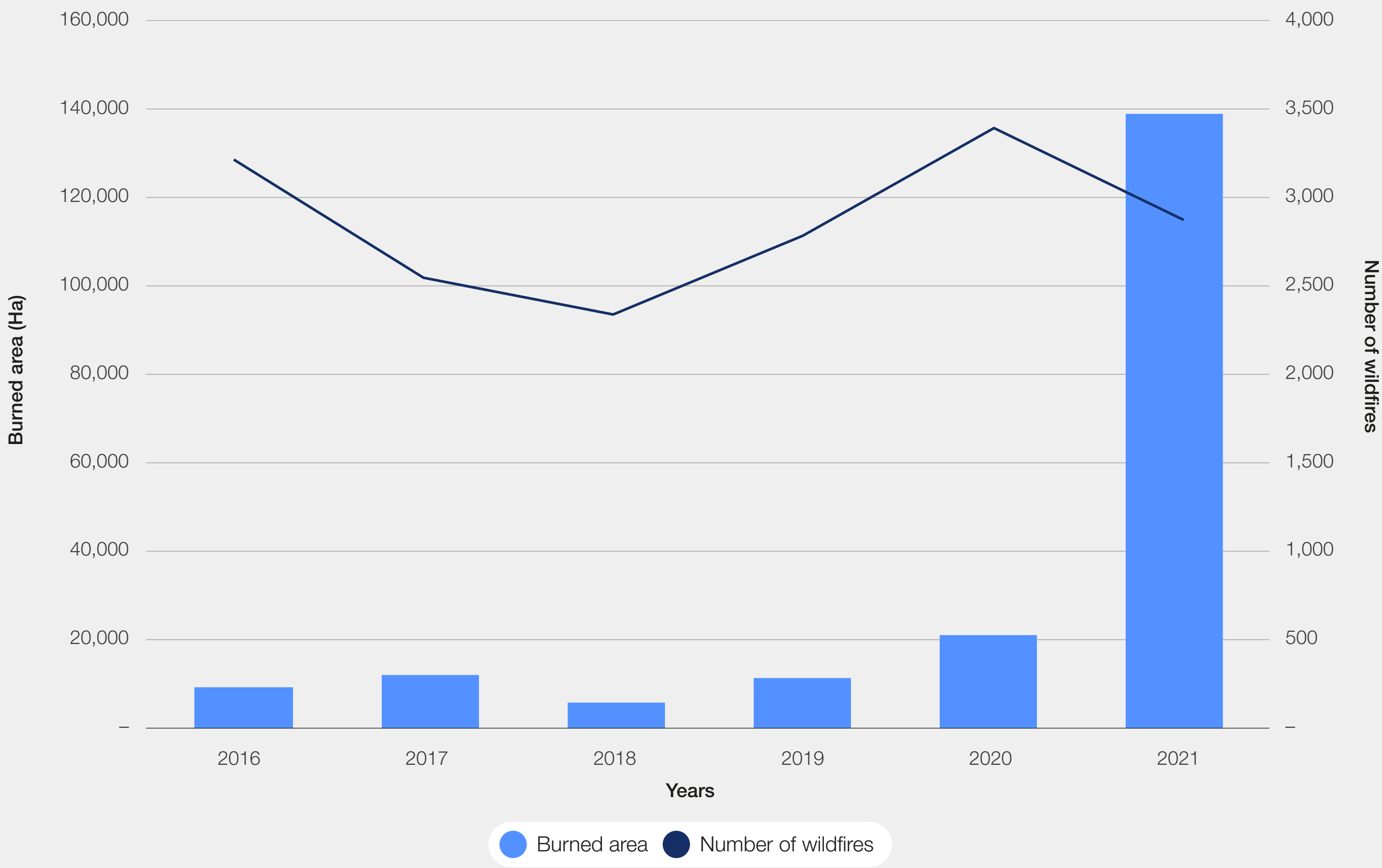
Introduction

139,503ha
Area burned in wildfires in Türkiye in 2021

Although all of the world is experiencing the adverse effects of wildfires and climate change, the Mediterranean region is one of the most wildfire-prone regions in the world. Each year, 80% of the total area burned in Europe is due to fires in Portugal, Spain, France, Italy, Greece and Türkiye.[37]

In 2021, a 139,503-hectare area burned in Türkiye – an area nearly the size of London.[38] Although over the period 2016–2021 the number of wildfires has not fluctuated much in Türkiye, their severity has increased dramatically, as shown in the chart below.[39]

FIGURE 7 | Number of fires and burned areas in Türkiye between 2016 and 2021



Source: KoçDigital from TMAF data: https://www.ogm.gov.tr/tr/e-kutuphane/resmi-istatistikler

KoçDigital Türkiye pilot: wildfire management process with FireAId

Like many countries around the world, Türkiye experienced the worst-ever wildfire season in the country's history in July and August 2021. Following these devastating wildfires, Koç Holding's aim shifted to doing far more than just helping alleviate the short-term impacts of this disaster. A pioneer of the digitalization agenda in the Turkish private sector, the company wished to offer its AI-related capacities to the country's relevant public bodies to help them better predict and fight more efficiently against future wildfires. And so Koç Holding launched the FireAId Project as a global initiative of the World Economic Forum AI and ML Platform in collaboration with the Turkish Ministry of Agriculture and Forestry (TMAF) and the Centre for the Fourth Industrial Revolution Network.

In conversations with the TMAF, it became apparent that there was an urgent need for an advanced analytical model that proposes smart logistical planning for fire suppression as such planning is totally dependent on expert opinion. In keeping with the need to relax this dependence and reduce human errors, the FireAId project aims to provide the ministry with a decision support tool that relocates resources optimally during wildfires. During a wildfire, it is critical to shift resources from the surrounding areas to the fire area as quickly as possible without endangering these regions. This calls for a chain of relocations from the low-risk regions to the high-risk regions. Therefore, any decisions should consider the wildfire risks in every region, which necessitates a wildfire risk map that is updated dynamically and feeds information into an optimal resource allocation model. A wildfire risk map is also beneficial for daily planning of patrolling fire teams and fire-prevention maintenance.

The FireAId project has been conducted in two phases:

– In the first phase, wildfire-related dynamic and static datasets were used to generate a risk map. The risk of wildfires was categorized under two types: ignition and severity. While the first represents the probability of having a wildfire, the second describes the severity of the wildfire. The FireAId project is focused only on the risk of ignition.

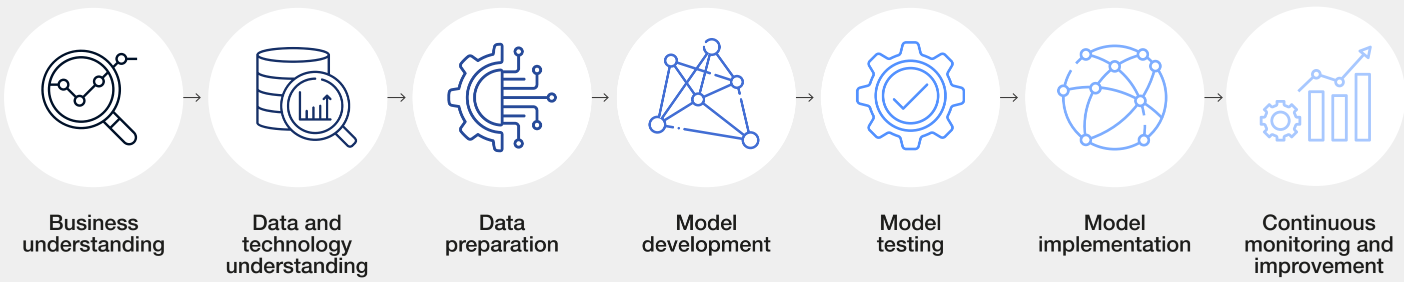
– In the second phase, the risk map was used to create an optimal resource allocation model after ignition.

> A pioneer of the digitalization agenda in the Turkish private sector, the company wished to offer its AI-related capacities to the country's relevant public bodies to help them better predict and fight more efficiently against future wildfires.

To develop the models, a pilot region was selected with the help of wildfire experts and officials. Following data analysis and interviews with stakeholders, the South Aegean and West Mediterranean parts of Türkiye were selected for the pilot study. Some 25% of Türkiye's wildfires had broken out in that region, corresponding to 75% of total burned area in the years 2010–2021.

Initially, the TMAF used a wildfire risk tool, owned by the Turkish Ministry of Environment and Climate Change, that was based only on meteorological parameters. However, domain experts and fieldworkers were aware that meteorological parameters per se are not satisfactory to estimate wildfire risks. Even though such parameters have a huge impact on the ignition and spread of wildfires, static parameters such as energy transfer lines, vegetation and topographical characteristics also have significant effects. Therefore, there was an urgent and fundamental need for a risk map that takes static and dynamic parameters into account.

FIGURE 8 **KoçDigital project steps**



Source: KoçDigital

Initial state

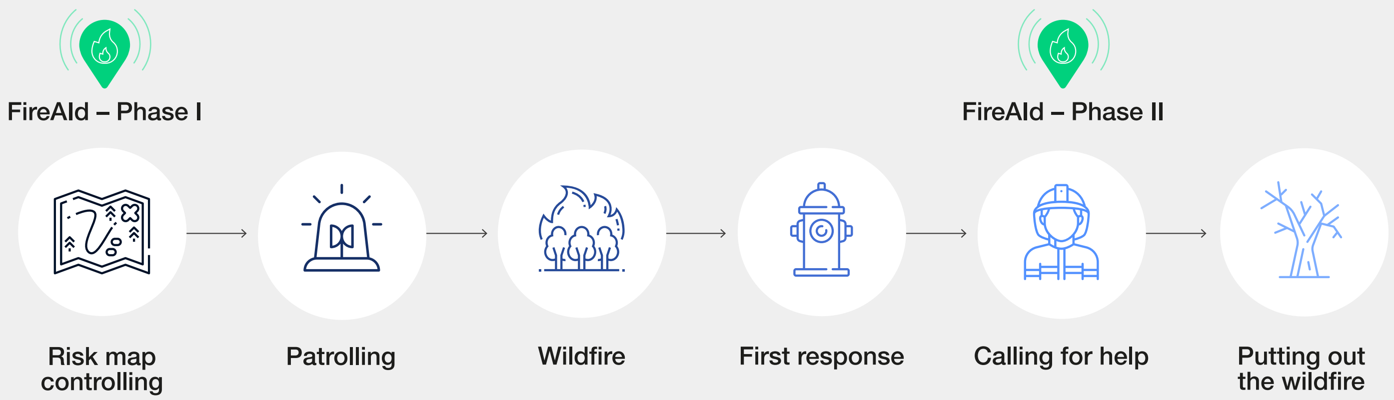
First, the meteorological risk map was checked by experts in the early morning and the regions at risk were determined daily. Based on this, responsible parties in the region were notified about the risks and the areas to be patrolled were planned. If a wildfire broke out at some point, firefighting teams conducted the first response. Depending on the severity of the fire, the teams might call for help from the neighbouring regions. Based on these experiences, it became clear that the first 15 minutes are critical in controlling a wildfire and that in the case of a serious ongoing wildfire, the response time for the relocation of firefighting teams is vitally important. Initially, the TMAF handled cooperation between the regions manually, guided by expert opinion and based on past experiences. To reach the wildfire location as quickly as possible, the team manager first called on neighbouring regions for additional resources (auxiliary resources/teams). But when these regions shared their resources, they became prone to wildfires themselves. Therefore, just immediately after the departure of auxiliary teams from these regions, the teams were replenished with resources from their own neighbours, which are further away from the wildfire locations. At first there were no decision support tools for the resource relocation process.

Modelling approach and performance metrics

As mentioned above, the project has two stages with different modelling needs. The first phase, in which KoçDigital built a wildfire risk map, required a machine learning model that learns from historical fire data. The predictions of this model were then fed into an optimization model that relocates resources faster and with a higher degree of safety during a wildfire.

FireAId's second phase aims to help decision-makers relocate resources according to the fire risk status of the region as well as the response time. TMAF's wildfire response process flow is shown in Figure 9.

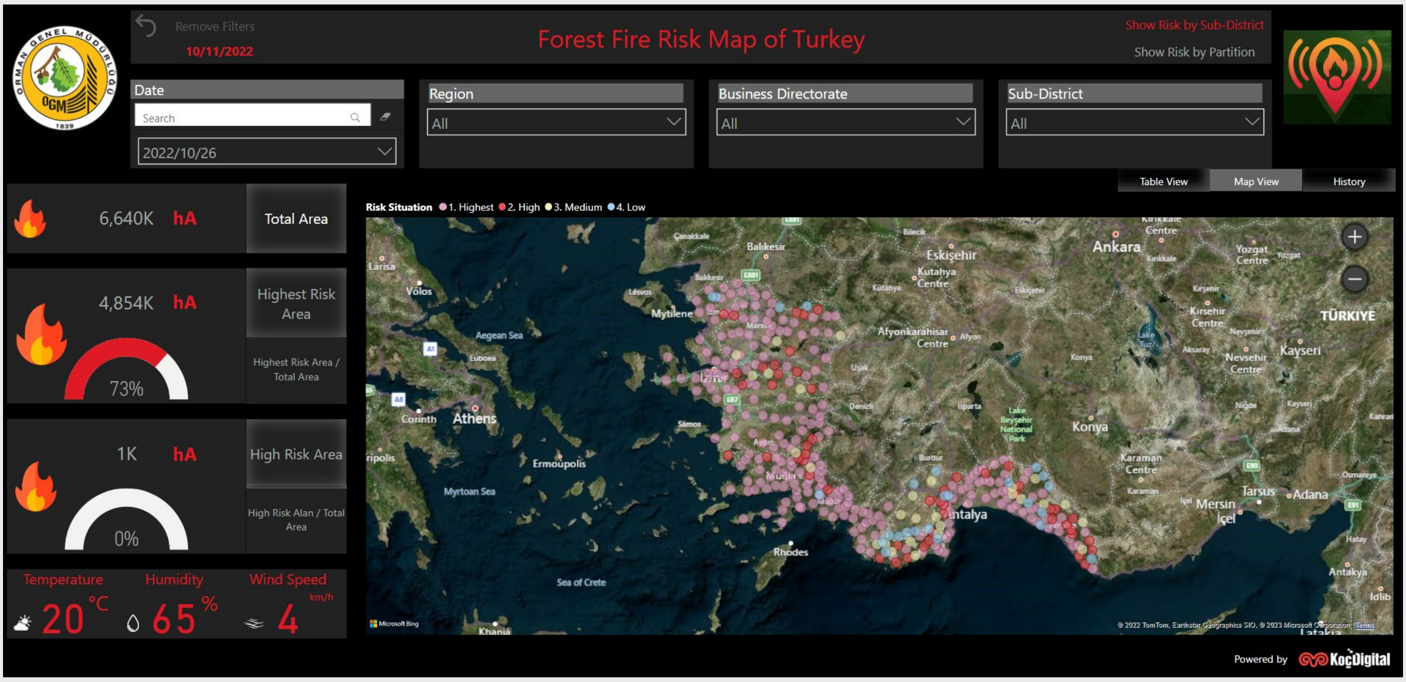
FIGURE 9 | Wildfire response process flow at TMAF, where FireAId modules are used



Source: KoçDigital

Future fire occurrence/risk prediction is a particularly challenging task. KoçDigital has built a binary classification model in which fire instances are classed as positive events and non-fire instances as negative events. The model output is a probability for fire occurrence, which is then converted into four classes: very high risk; high risk; medium risk; low risk.

FIGURE 10 **Dashboard for forest fire risk map of Türkiye**



Source: KoçDigital

The pilot study focused on the South Aegean and West Mediterranean parts of Türkiye, which account for 44,000 km^2 of land. The static geography data consisted of tree type, age of forest, closeness of trees and elevation. KoçDigital has combined the geographical data and 10 years of daily meteorological data on wind speed, humidity and wind direction with historical fire data. Additional data sources can be seen in the data section below.

The pilot region was studied using two different levels of granularity. First, KoçDigital considered the subdistrict directorates – there are 332 of these in total in the region of interest. The second level of granularity is the “partitions” within the subdistrict directorates – each directorate was divided into around 300 partitions containing similar sizes of forest areas. In total there were 66,394 partitions.

To understand the model’s capacity to capture risk, as an accuracy metric, the percentage of correct predictions for fire and no-fire instances was considered separately. Wildfires are rare instances and it is hard for any statistical model to catch them. As capturing fire occurrences is more important than no-fire occurrences, the model is tuned so that the regions labelled as high-risk areas cover most of the wildfires that occured, which results in a lower prediction accuracy of no-fire instances. Therefore, this tuning process should also capture an acceptable amount of no-fire instances, as it would not be useful to label everything as high risk for resource allocation.

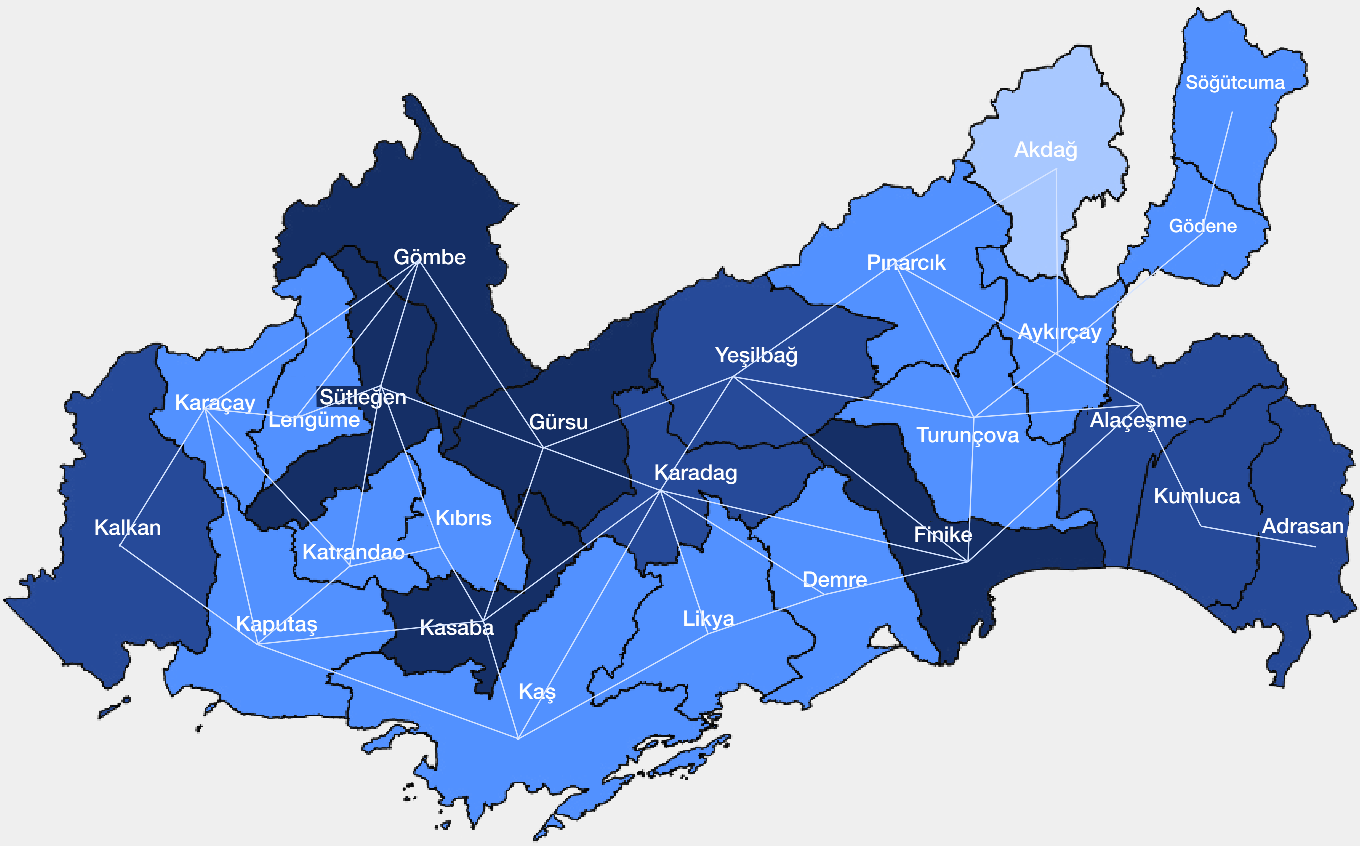
The meteorological data is received hourly from weather stations. In addition, a five-day weather forecast is updated every evening. The model runs twice a day, once in the afternoon with actual weather data and once in the evening for the following five days using the forecasts. Notifications of fire events are also received daily from the TMAF and the model is periodically retrained as new fire data accumulates.

After the completion of the risk map, KoçDigital was able to model the optimal resource allocation problem. There are 332 subdistrict directorates that hold their own wildfire resources. In current applications, when intervening in a wildfire, the neighbouring subdistricts share their first teams and resources as soon as they can, in order to fight the wildfire. This makes the neighbouring subdistricts vulnerable to potential new wildfires and, therefore, their resources need to be reinforced by other subdistricts that are further away from the fire location and face less risk of new wildfires occurring. This creates a network of subdistricts that share their resources with each other and, therefore, the problem can be modelled as a network flow optimization problem, which is well studied in the literature. This enables KoçDigital to reach a solution quickly and then easily scale the solution to larger areas.

Once an expert feeds the application with the wildfire location and the necessary amount of resources to fight the fire depending on the severity, the model will create the fastest and safest network of subdistricts that should share their reserves. This will help the experts to take decisions and reduce the amount of expertise needed to address the resource relocation problem.

> **With the wildfire risk mapping and logistic planning project, in which Koç Holding's advanced analytics and artificial intelligence capabilities and our know-how have combined, we have incorporated new technological advancements into our organization. Prior to this, only meteorological variables were used in risk mapping, but as of now static and meteorological datasets are combined. In addition, response time is one of the critical metrics in firefighting. The logistic planning part of the project enables us to reduce response time with less risk.**
>
> **We have been working on extending our pilot [throughout] Türkiye. We believe that extending FireAId to other fire-prone counties with the support of the World Economic Forum will help the fight against wildfires.**
>
> Bekir Karacabey, Turkish Ministry of Agriculture and Forestry, General Manager

FIGURE 11 **Resource transfer network of subdistricts**



Source: KoçDigital

What have been the key enablers?

Data

The initial geographical dataset covered 512,000 grid areas and included data on a variety of aspects, with varying levels of granularity, such as tree types and density, elevation and power transmission lines. Historical fire data included the location and date (since 2010), size and duration of fires and the resources used for intervention. Different types of forests and land use were also considered as well as meteorological conditions (see Figure 12).

FIGURE 12 **Features used in the fire risk model**

Flora and land use

Flora/land features
(summarized in 20 categories)

– Coniferous forest (pine, cedar etc)
– Deciduous forest (elm, maple, willow, etc.)
– Mixed forest
– Swamp
– Rocky
– Damaged forest
– Habitation
– Farm area
– Quarry
– Age
– Closeness

Total ~400 features

Land use types

– Rocky, sand, gravel
– Forest nursery
– High forest, coppice forest
– Burned forest
– Plateau
– Open area
– Swamp
– Forest depot
– Quarry
– Facilities
– Road
– Water
– Pasture
– Settlement
– Agricultural land
– Graveyard
– Fire-stop zone

Terrain features

Terrain

– Elevation
– Aspect
– Slope
– Power transmission lines
– Highways
– Forest roads

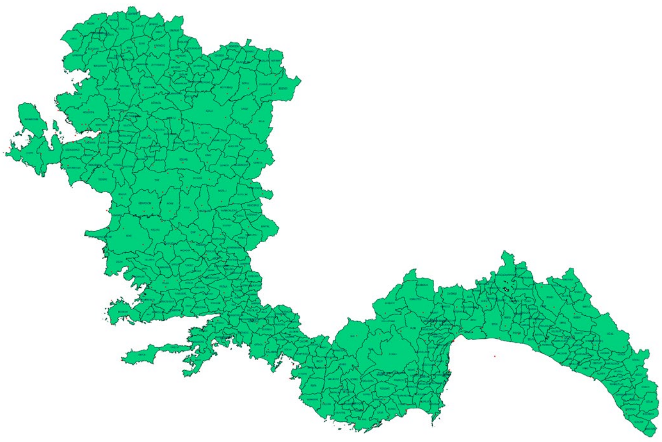
Weather data

Daily weather data

– Minimum temperature
– Maximum temperature
– Minimum humidity
– Maximum humidity
– Maximum wind speed
– Average wind directions

Going back to 2010,
5-day forecast

221 weather stations in the area of interest



Source: KoçDigital

KoçDigital built a diverse team who could successfully apply AI and optimization principles in this field.

Algorithms

In the first phase, after comparing different machine learning models, the data scientists decided on a tree/rule-based gradient-boosting algorithm as the best-performing model. Although this model lacks the simplicity of the regression models used in the literature, they believe that the increase in the accuracy compensates for the complexity of the model and is better aligned with the project objectives.

For the second phase, to ensure alignment with the TMAF's current practices, the data scientists considered the subdistricts in the pilot region as a network of wildfire teams that share resources with each other. This approach enabled modelling of the resource allocation problem as a minimum cost network flow problem, which in fact can be solved very efficiently by linear programming. This simple formulation resulted in fast and scalable solutions.

Knowledge-sharing and collaboration

It is obvious that combating wildfires requires collaborative action and cooperation among different parties. On the regulatory side, the main actors are ministry officials and government, while ministry officers, fieldworkers and firefighters are the field experts responsible for planning and maintaining wildfire-related activities. Academic studies also play a crucial role here, creating knowledge and generating theory that later turns into practice. To ensure the project covered all aspects, KoçDigital built a diverse team of project managers, business consultants, business intelligence consultants, ML engineers, data engineers, data scientists and software engineers who could successfully apply AI and optimization principles in this field.

Climate change and wildfires are global problems and hence international collaborations and knowledge-sharing are immensely significant. Different parties have been working on similar issues around the world. Accumulating knowledge at a single point facilitates the adaptability of final products in different regions and accelerates this process, helping build teams with essential expertise, create new resources, intensify synergies and raise global awareness.

Customer support

It is always important to have a good customer who provides buy-in to the project and supports the development team throughout the entire project life cycle. Having the customer's oversight and guidance is essential in determining the project's objectives. For the FireAId project, the TMAF proved to be a highly motivated, committed customer, providing the necessary resources (e.g. data, subject expertise etc.) and currently piloting AI models in the field.

What were the challenges and barriers?

Data accuracy, accessibility and availability

The required data came from two ministries, the TMAF and the Turkish Ministry of Environment and Climate Change. This duality of sources caused delays in accessing the data and required new agreements between different government bodies. It was also important to maintain constant data flow and to avoid data compatibility issues. Meeting these demands required a collaborative effort, and KoçDigital's approach was to keep the stakeholders, domain experts and data providers involved and informed at all times.

One of the targeted outputs of this project was to set standards for future data collection. A major challenge was dealing with the lack of up-to-date or high-resolution data in some cases. As the data requirements become better understood, a plan could be devised to integrate more data resources – for example, satellite or drone images to accurately map forest-floor fuel status or data from mobile phone towers to estimate changes in the population. Another interesting data-gathering approach with significant potential is crowdsourcing. For instance, it may be possible to acquire detailed, up-to-date information about forests using smartphone apps and volunteer hikers.

80%

of fires in Türkiye are caused by human activity

Unpredictable human behaviour

Forest fires are highly affected by human behaviour, which causes some randomness in fire occurrences. Some 80% of the fires occurring in Türkiye are caused by human activity, according to TMAF field workers. Unpredictable human behaviour makes it challenging to predict the risk factors. Better methods of measuring (average) human activity in at-risk areas would increase the accuracy of risk models. KoçDigital has used features that help predict human activity such as roads, farm areas, population density and distance to the sea. However, globally this remains one of the main challenges in wildfire risk prediction.

Imbalanced dataset

A major bottleneck for algorithm accuracy is an imbalanced dataset. Usually no-fire instances are much larger than fire instances. In more granular terms, at subdirectorate level, that is 1 in 100, while at partition level, it is much larger, in the order of 1 in 30,000. This necessitates a consideration of different under-sampling and cross-validation scenarios.

Scale of data

Partitioned areas may be as small as a few kilometres in length (in the dataset, there are a total of 66,394 partitions). If 10 years of historical data is considered, that is multiplied by 3,650 (365 days times 10). It is possible to go even lower in terms of granularity since the original geographical dataset contained a total of 512,000 grids for the pilot region. That constitutes a massive amount of data and requires parallelization for feature engineering and model training.

Piloting results

The first phase of building a dynamic wildfire risk map in the KoçDigital pilot is completed and in use. The organization is now in the process of gathering valuable feedback from users so it can constantly improve the models and the user interfaces. The second phase involves refining the model, with KoçDigital consulting experts from the TMAF.
The pilot, one of the biggest non-profit private-sector/government collaborations in Türkiye, uses expertise, labour and data from two ministries and an AI company. Dealing with disasters using state-of-the-art technology requires the collaborative effort and expertise of many institutions nationally and internationally. Data quality is the main concern in successful AI/ML projects; dealing with data collected manually by people requires them to have sufficient awareness about datacentric solutions in order to maintain the accuracy and uniformity of the data. The project is expected to contribute to this culture in Türkiye, as well, because it will promote greater collaboration among institutions.

“ Dealing with data collected manually by people requires them to have sufficient awareness about datacentric solutions in order to maintain the accuracy and uniformity of the data.

Two main issues in relation to meteorological data are the accuracy of past records and the granularity of weather observations (and forecasts). It is difficult to increase resolution for historical data. However, for future studies, a data collection and forecast model that extrapolates meteorological observations and forecasts to smaller grids can be developed, working in collaboration with local authorities.

As described in the previous section, in order to evaluate the performance of the models, the KoçDigital team looked at recall for fire and no-fire events separately. KoçDigital's intention is for the model to catch as many fires as possible without labelling everything as high risk, which would render the model unusable for resource allocation.

For training the data, different strategies for sampling and filling the missing data were used. Meteorological data has proved to be particularly difficult since there are gaps in the data received from different stations. Moreover, it is difficult to collect the meteorological conditions at the exact locations of past fires. Several approaches have been tried: looking at the number of nearest stations, using median for temperature, using average value from different stations in the area, manipulating temperature values based on elevation differences between the fire location and the nearest weather station.

To maintain consistency between the models with different granularities, the risk scores for the lower-granularity model (i.e. subdistricts), were used as a feature for the model with a higher number of divisions.

Based on the TMAF's input for relevant features of risk, a monotonic constraint parameter for certain variables was included.

The testing was conducted on data from the fire season (the months between April and October) of the previous year, using whole data without doing any sampling. With the data at hand, recall values of 0.8 for fire and 0.5 for no-fire events were achieved. While there could be room for improvement in terms of the restrictions of the data and fire dynamics, it is not expected to achieve significantly higher accuracy for the model.

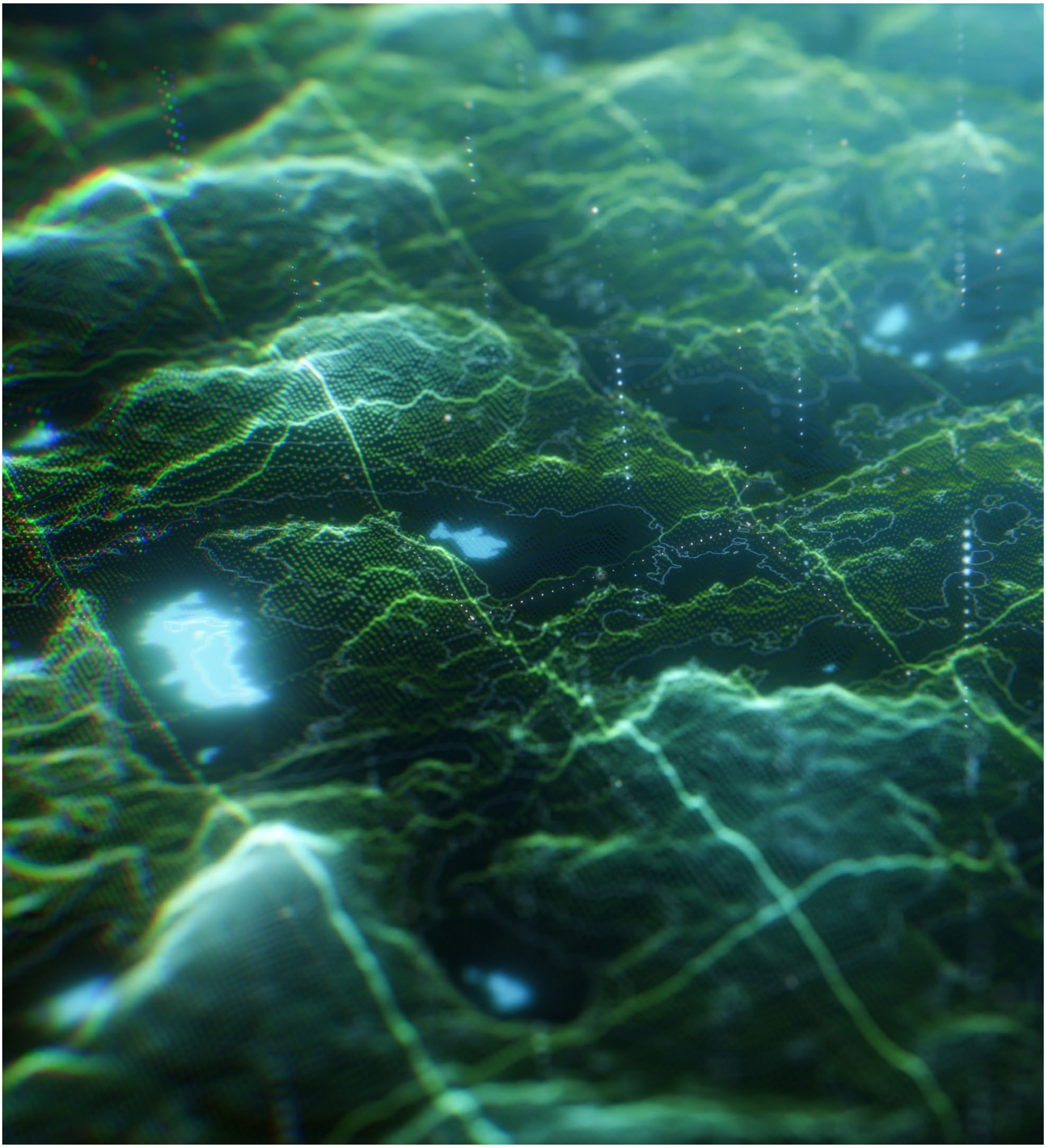
What is next?

As requested by the TMAF, KoçDigital will scale its solutions to cover all regions in Türkiye as the next step. Since the country has a diverse geography, this scaling effort will also provide experience that will enable these solutions to be applied to other countries. Another by-product of the risk map and resource allocation models built and the fire statistics gathered by KoçDigital will be providing assistance to the TMAF during its yearly resource allocation planning before the coming wildfire season.

Furthermore, data providers and piloting partners from the Mediterranean region are particularly needed because the similarities in climate and territorial characteristics may facilitate more pilot studies and encourage broader adoption of the AI applications already being developed by KoçDigital using the multidimensional data provided by the TMAF.

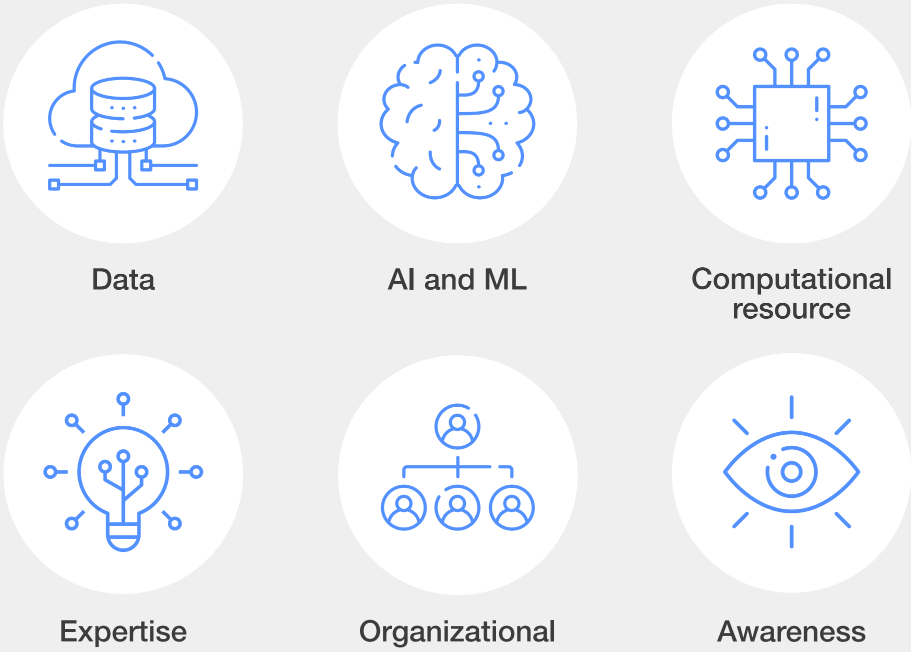
4 Impact at scale – barriers and enablers

As well as identifying the challenges in leveraging AI for wildfires, an approach will need to be found that enables successful scaling of AI models.



4.1 What are the barriers to scale?

FIGURE 13 **The six barriers to a successful solution**



Source: World Economic Forum

Data barriers

The 21st century faces enormous challenges – health, societal, environmental, even existential – but it does have one distinct advantage over prior centuries: an abundance of data. Data is recorded in unfathomable quantities using all manner of sensors all around the world – whether on the ground, in the air or from space. The question is how accessible and indeed useful that data may be.

For several problems in the field of wildfire management, fuel structure is a major data requirement. This data can be obtained from static maps that are updated regularly. Another approach would be using satellite image data to map the forest fuel status.

Freely available data tends to be of lower quality or frequency, especially in the case of satellite imagery. Taking a small tranche of land measuring less than 100 km^2, for example: the free version yields four images per month. Upgrading to daily frequency costs €20,000 per year – and that is for only 100 km^2 of land, generally too small to be of use in the wildfire context. Other sources may provide images free of charge, but at lower resolutions. The differences can be significant: 3 m^2/pixel for the paid version vs. 100 m^2/pixel for the free version. In addition, freely available data may not be well formatted, requiring resource-intensive pre-processing before it can be effectively used in models.

One challenge with satellite imagery is the cumbersome "stitching together" of neighbouring snapshots. It is not inherently obvious where each image belongs spatially, relative to the preceding image. Some APIs have cleverly solved this problem, but they (justifiably) charge for this service. Costs may be entirely reasonable when surveying a small patch of land, but become significant, even prohibitive, when covering an entire country. For this reason, multistage models are necessary. The first model uses inexpensive data with geographic coordinates to identify where to limit the use of expensive, high-quality satellite image data. Limiting the image processing to the "hotspots" reduces both data acquisition costs and computation resource requirements to process the data.

Some of the problems associated with satellite imagery are alleviated by using weather data instead. For example, satellite image data is generally needed to gauge the degree of "fuel" in a region that a fire may consume. However, it is possible to lower the frequency at which satellite data is required – and for other cases alternatives can be found; incline of terrain and other important geographical features, for example, can be obtained from map data (fire tends to burn uphill).

Weather data can also be a valid substitute – providing humidity readings as an alternative to infrared spectrum satellite images. It also requires less storage space and computational resources to process. Yet weather data has limitations, too, and there are different sources, each with its relative pros and cons. As noted, ERA5 weather data has a rich feature set and history going back to 1950, but there are large time intervals between updates – from four to six weeks. By contrast, NOAA weather data includes both actuals and forecasts and is updated several times per day, but it offers fewer features and only two years of history.

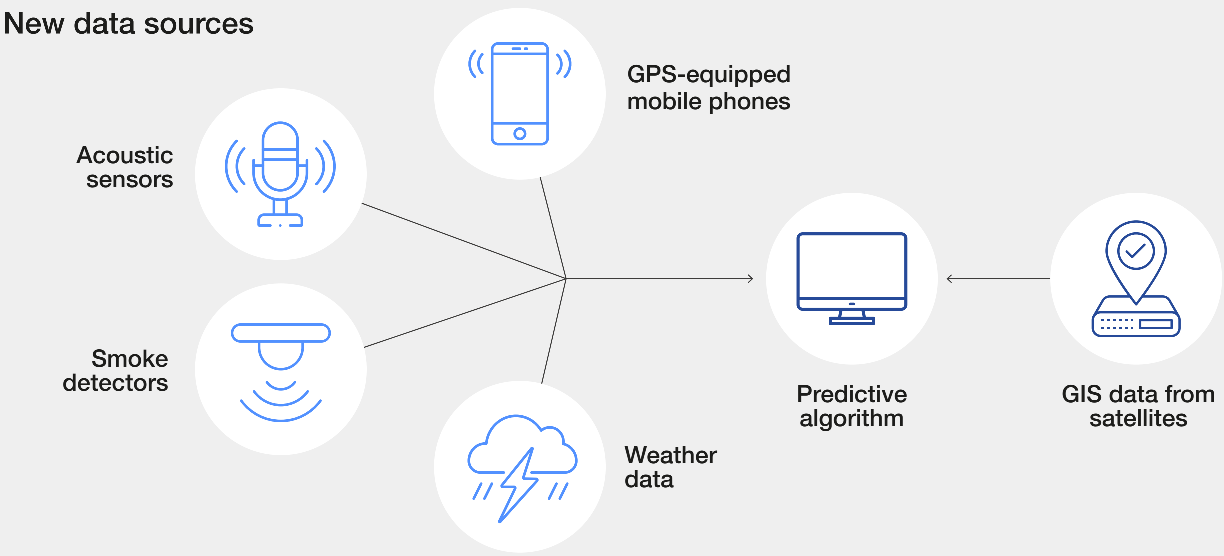
Other data sources might prove more promising, but will require dedicated effort in dispatching new sensors:

– Acoustics – microphones being used to track wildlife applied to the different sounds of fire

– Smoke detectors – at select locations, depending on their sensitivity outdoors

– Human sightings reported by mobile phone with GPS coordinates

FIGURE 14 **New data types supplement old forms, helping to address the technical difficulties of wildfire prediction**



Source: World Economic Forum

Regarding the data, there are three main challenges: 1) access, usability and integration of data sources; 2) accuracy of data; and 3) sparsity of fire events in the data.

While these will constitute problems for scaling (as further explained below), another major bottleneck is the **lack of global standards for data collection and data format**. Inconsistent data sources and types pose a challenge to disseminating risk (or other) models into additional geographies. Hence, it becomes crucial to form a community from different countries to identify the required data and format in different geographies for different solutions (fire risk, danger, resource allocation, etc.) and to set guidelines for data preparation for analytic studies. A global hub for open-source data for the future can be envisioned; however, for the moment, most of the data work is specific to a country or region.

Data accuracy, and access and integration

Using accurate data plays a major role in the predictive power of ML algorithms. Factors that contribute to wildfire ignition include historical fire locations, cause of fire and weather conditions, as well as fuel structures. It is imperative to ensure that data is up-to-date and accurate. However, due to faulty recordkeeping or the difficulty of maintaining sources, it is likely that gaps will occur. While these gaps will be specific to local ministries and landscapes, a global guideline for improving data accuracy can be established. For instance, new sources such as satellite images and drone footage can be used to map and gauge the changing fuel-structure conditions. Using local studies, a global recommendation for the required technology, algorithms and types of data can be established.

Another way to improve data accuracy and keep it up to date could be crowdsourcing. Walkers with smartphone apps can easily update forest flora information using AI-powered imaging models. This would also be a way to promote awareness about wildfires among the public.

Alternative data sources used to track human activity – a significant factor for predicting the outbreak of wildfires – are often subject to differing data privacy standards across the globe. One example is mobile phone data, which may be collected and analysed in one jurisdiction, but not in another – at least not without intensive guardrails and anonymization routines.

Stand data maps[40] are extensively used in forestry. The wildfire risk and threat are highly related to the age, closeness and type of the forest. Especially for risk calculations, stand maps are of major importance. Unfortunately, these maps are made by hand by field workers. Creating and maintaining such maps is not a straightforward process for a variety of reasons. For one thing, making them requires significant experience in the field – the type of the trees, borders of the forests, age of the trees and other forest properties should be represented. In addition, map formation is not a one-time job. The maps have to be updated regularly, and this is a time-consuming and demanding task for the field workers. To scale up a project, the very first burden is to ensure **data quality and recency**.

Another barrier in terms of data is **confidentiality**. For some use cases, data charting energy transfer lines, topography and highways is required. For most countries, these datasets are considered confidential. Accessing those datasets, as well as ensuring data security, is another important limitation in this context.

Finally, it is worth noting that AI models are developed based on the data at hand. It is necessary to have past wildfire datasets available to use. These may contain insufficient or inaccurate information. Before scaling up, it is necessary to have **reliable historical wildfire data at hand**.

In summary, the key challenges are:

- **Availability** – while some data sources are international in nature, others are region-specific: using them limits transferability; not using them could impede model predictive power
- **Accessibility** – infrequent or lower-quality data is widely available, but of little use. The useful equivalents are costly to obtain, store and process
- **Volume** – some data formats, such as satellite imagery with its 2D resolution and multiple spectral bands, are inherently bulkier than others
- **Frequency** – some data sources are updated too infrequently to provide timely warning or useful information in the dynamic context of spreading wildfires
- **Content** – some data sources suffer from a sparsity of features, others from lacking historization (e.g. they record the actual values, but replace prior forecasts with newer ones)
- **Compatibility** – differences in frequency, feature set, even formats, complicate the combination of data

“ Factors that contribute to wildfire ignition include historical fire locations, cause of fire and weather conditions, as well as fuel structures.

AI and ML barriers

Machine learning is an unparalleled tool for mapping complex, non-linear relationships. However, achieving high levels of performance is not a trivial task. As previously mentioned, forecasting the attributes of wildfires requires the modelling of non-linear and complex relationships. A highly predictive model will more likely than not also be a complex one. Complex models are derived from substantially more training data. (In a world with limited wildfires, it is a non-trivial task to obtain sufficient training instances required for a deep learning model.) Model optimization with its many iterations and even inference after deployment will demand more computational resources.

Another issue is generalization: ensuring that the model performs well in all instances it encounters. Many questions arise. Should multiple models be trained? If so, should they be split across geographical areas, terrain types, or even political boundaries? Many vital features for prediction are published by national public organizations for their own regions and the same features are often collected and standardized differently. Where bespoke models may promise better performance through the inclusion of local features, they cannot rely on local features alone – the data will generally not be sufficient. This introduces the challenge of designing the model to integrate modules on to a common core, which has been trained on a larger – if less regionally optimized – set of universally available data.

AI models not only learn from collected data but can also be designed to create, augment or update datasets.

A very concrete problem is the element of randomness to wildfire ignition. Even under perfect conditions for a wildfire, it is quite possible that nothing happens. In the majority of cases, ignition is triggered by human activity (cigarettes, campfires) or by lightning strikes. Each of these ignition sources carries high degrees of uncertainty. Averages aside, how can a model predict whether *any one person* will properly extinguish a cigarette, or where lightning will strike *at any given moment*? The difficulty in modelling the randomness factor affects how to assess the model. Is it realistically good enough to correctly identify the right combination of conditions for a wildfire, without penalizing the model if no ignition ultimately occurred? How useful is that to firefighters?

As has been seen with many efforts around the globe to create ML models for wildfire prediction, the question of the possibility of transferring knowledge between these trained models arises. Such models are tuned and trained with local data and perform very well in specific regions, but it is not straightforward to transfer the relevant information captured by these models on the relationship between wildfires and their causes to other parts of the globe. Global models that capture the common traits in the data from local regions may give a developed starting point for local AI teams to build upon, but there is a definite need for better solutions to this problem to ensure that these models can be adopted by local authorities without too much investment in data collecting and model-building.

AI models not only learn from collected data but can also be designed to create, augment or update datasets. For example, AI models trained to recognize types of forest or signs of human activity from aerial images can subsequently annotate new "unlabelled" imagery, automatically enriching it for AI models trained to perform other tasks. Globally available and easy-to-access public data would also result in open-source applications of AI in the domain of wildfires.

Computational resource barrier

Spatiotemporal forecasting is a demanding problem: weather systems are extremely non-linear and chaotic – they diverge from input conditions quickly and all features have complex relationships with each other and with their surroundings.

Traditional weather forecasting models work deterministically by modelling the atmosphere as a mesh and allowing surrounding connections of each node to influence its value through governing equations. Historically, this has been one of the most intensive computing use cases. As computing resources have expanded, the granularity of the mesh has increased, improving the accuracy and potential horizon of forecasts. This has direct parallels with an ML-based approach to a spatiotemporal problem: it is extremely computationally intensive, and performance improves as the resolution and depth of the model increase. When thinking about it this way, this problem will always be computationally limited where training data of comparatively high-resolution data is available.

Even when building and deploying a model at a reasonable resolution and, by extension, complexity, there are pragmatic issues specific to this use case. The first is that training such a model requires powerful hardware – training instances have high memory requirements as they typically have many features and span large areas of land. Training the model in memory requires massive amounts of random access memory (RAM), typically more than is commonly available on the premises. A common solution to this is to run it in the cloud.

Cloud providers offer scalable computation and memory resources; however, retraining and serving such a model on such a platform may still not be appropriate. Even after code optimization, the cloud resources required are graphical processing units (GPUs) and compatible, fast RAM. Whether on the premises or in the cloud, resources such as these are expensive – prohibitively so for most end users, including NGOs or underfunded government entities. Beyond training, even post-deployment inference requirements are considerable. For example, in a medium-sized country such as South Africa, an area of 1x1 km resolution corresponds to 1.22 million data points to forecast at any one point in time. Add the time-series component projecting into the future, and the figure grows by a significant order of magnitude.

Technical expertise barrier

Computational advances in the late 1980s gave way to finite element modelling for machine components, presenting mechanical, aeronautical and civil engineers with new tools to prototype and test structures before incurring manufacturing or construction costs. The past decade has seen tremendous advances in computational power, led by the discovery that GPUs from the computer gaming industry are ideally suited to exactly the sort of floating-point mathematical operations required for finite element analysis at scale. Pioneering GPU companies such as NVIDIA built not only the hardware but also the software required for engineers and computer scientists to access that computational power. Frameworks such as NVIDIA's Modulus can be combined with AI models to deterministically represent the physical behaviour of fluids, smoke and fire. This is exciting because more can be made out of less data. AI need not be used to derive all of the rules from data, as some of the rules (the laws of physics) are known already. Where data continues to be required is in understanding the interplay between environmental, geographical and temporal variables. Weaving together rules- and data-based approaches into a type of "hybrid intelligence" allows a focusing of AI efforts on what can reasonably be predicted – leaving the rest to Isaac Newton and his peers.

Organizational barriers

Wildfire management is a multistakeholder system – a challenge in its own right. In the field of wildfires, there is continuous interplay among bureaucrats, field experts, academicians, international organizations and technology experts. Wildfire management can be successful only if multiple parties come together, each contributing vital expertise and resources. The strongest teams are diverse , with each contributor able to jolt the others out of their short-sighted comfort zone, allowing real innovation to take shape. To achieve this, stakeholders must be brought together. Firefighters must be able to see that this is worth their precious time. Technology partners must convince them that "high-tech" need not mean "complicated" or "more work". Ministries must actively join the conversation, playing the role of enabler, removing barriers to progress. A dynamic in which firefighters or technology partners request funds to enable focused work is the wrong one. Ministries must be so involved that they create a sense of urgency, spot opportunities to accelerate and provide the financial means to do so. Projects such as wildfire risk management are complex, and require focused attention. Volunteer work is fine to get things going, but it will be fraught with difficulties – yielding to other priorities, making slow and unsteady progress. Government ministries can change that.

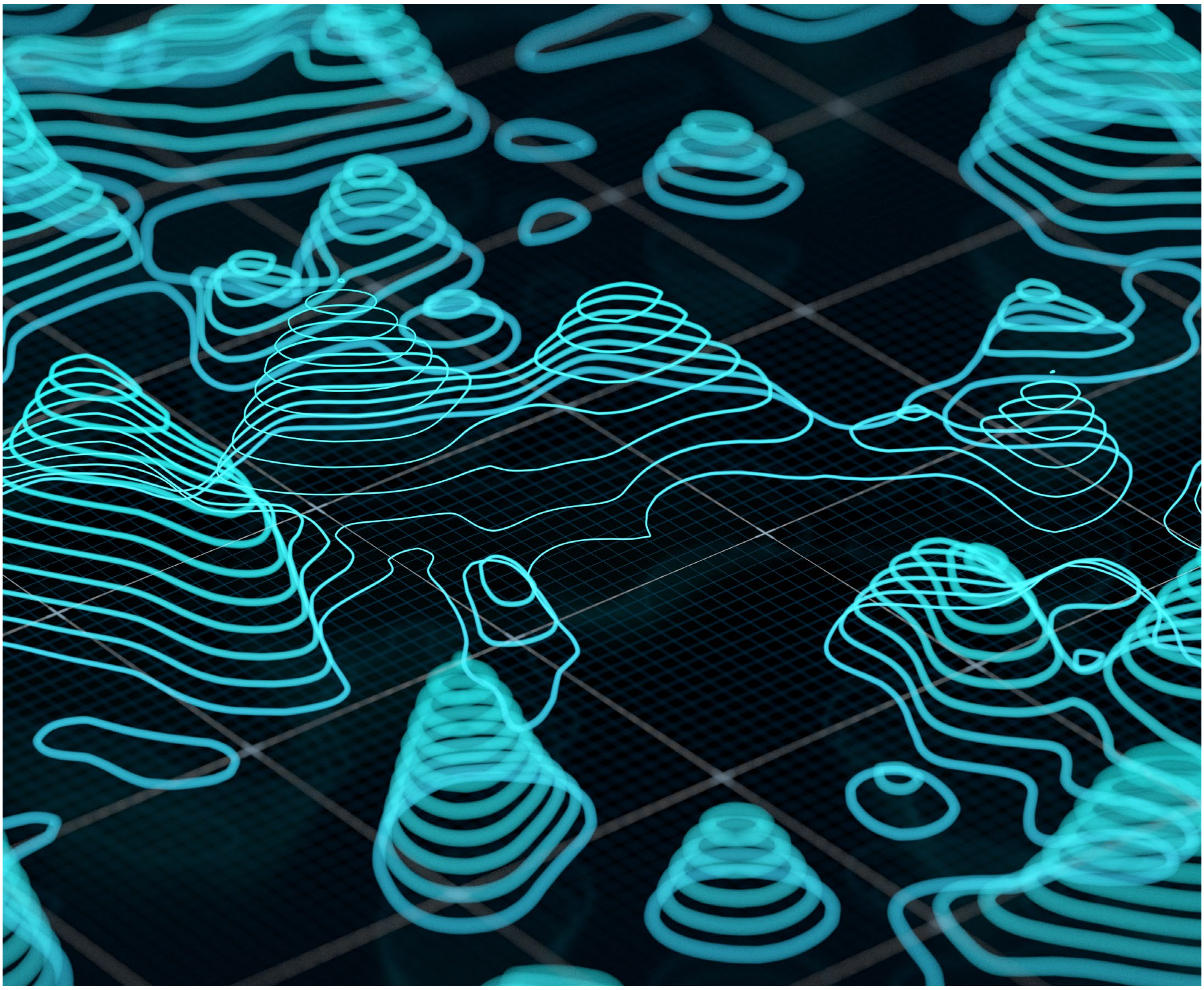
The wildfire management system can be evaluated as a sociotechnical system containing "social" and "technical" aspects that are interdependent parts of a higher and a complex system. Therefore, there is a need for comprehensive management and integrative solutions. In other words, none of the parts (social and technical) should be overlooked. While the "social part" of the system represents regulations, laws, procedures, people, culture and goals, the "technical part" contains infrastructure and technology.

Wildfire risk management presents many technical hurdles. Yet barriers persist beyond the technical. Technology-first approaches seldom have the impact of problem-first approaches: researchers, data scientists and engineers are a smart crowd, but they need the voice of the customer to avoid the trap of becoming absorbed by the technical challenge over the usefulness of their endeavours. End users keep the technical experts grounded, focused on the "impact that matters". This requires more than just the passive involvement of other stakeholders. Firefighters and ministries must play an active role in setting the vision and providing feedback.

To scale the project to the wider areas, it is crucial for all echelons and elements of the system to be taken into account. New technology applications often meet resistance when they radically change existing processes and the way of doing the job. Therefore, creating and maintaining a tech-savvy culture is essential to acceptance of tech-enabled novel approaches to familiar problems. Without the involvement and buy-in of all stakeholders, even the most technically impressive solution will not be used. New tools and approaches benefit greatly from user feedback. Scaling solutions to other regions is therefore as much a technical as it is a people/ cultural endeavour, especially in the context of AI, which evokes as much fear and distrust as it does fascination. The managers and bureaucrats should be aware of this "soft side" to technology projects, as "social" factors may be even more influential than technology in determining successful outcomes.

Awareness barriers

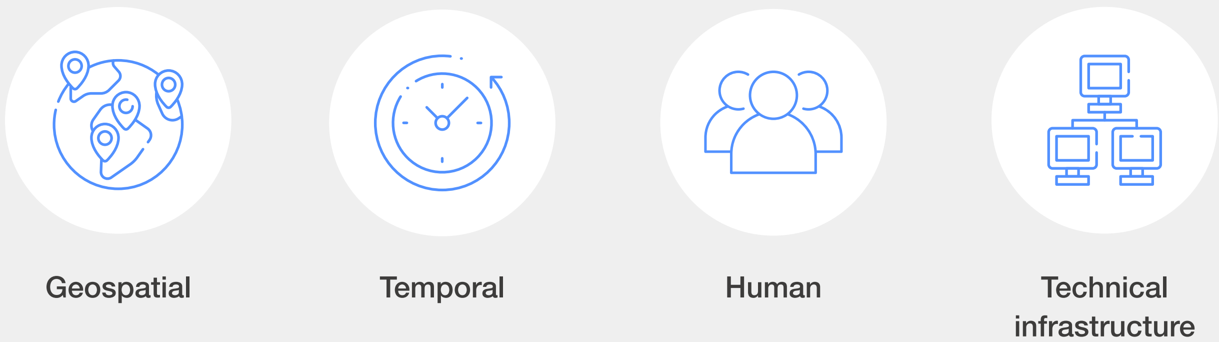
For this to work, all parties must be made aware not only of the problem but also of the possibilities of finding a solution, and the irrefutable necessity for multidisciplinary cooperation. Non-governmental organizations (NGOs) such as the World Economic Forum can and do play a vital role in exactly this context. The Forum's FireAId initiative is just one example where it actively shapes public policy in constructive directions. FireAId is tackling the awareness barrier at several levels. To start, it puts wildfire risk management on the agenda of international governments, if they are not already there. It opens dialogue between governments and large multinational corporations to identify critical areas of collaboration and support that are required and that empower the ministries of forestry or environment to play an active role in collaboration with the industry. FireAId serves as a reminder that climate change and wildfires are a global problem that will require global cooperation, and that everyone has a role to play in finding the solution.



4.2 What is needed to scale for the desired impact?

Developing a better AI model is one thing, scaling is another. The challenge of scaling lies in the model's geospatial and temporal dimensions. Unlike the AI model, scaling also has a human component – considering local requirements beyond the universal attributes of the baseline model. All four enablers of a successful solution – geospatial, temporal, human and technical infrastructure – are critical to the success of a global effort to combat the terrible consequences of wildfires felt worldwide.

FIGURE 15 **The four enablers of a successful solution**



Source: World Economic Forum

The first enabler for scaling is portability – the “geospatial” factor

While the cost of wildfires could very well justify local solutions, all regions affected by wildfires can realize benefits of scale by coordinating their efforts. This starts with connecting project teams, each focused on regional particularities, so they may learn from one another – mistakes and successes alike. Coordination continues with regard to the data itself. Regions collaborating on the standardization of metrics, use and placement of sensors, as well as database structures and APIs will deliver an immediate productivity boost for project teams. Teams across the world will be able to share not only high-level principles but also share at the detailed practitioner level, eliminating the need to reinvent the wheel for essential “plumbing” tasks, such as creating robust data pipelines. Efforts expended on “plumbing” should not be underestimated. A massive 85% of data science and AI projects (in general, not limited to endeavours such as wildfire risk) are estimated to deliver deficient results or end up restarting as data management projects, when teams discover that the data needed to achieve the original AI project’s goals does not exist or is not accessible in the manner required.[41] In the specific case of wildfire risk, the volume of data to be processed can quickly become prohibitively expensive to source, store and process. A significant step towards lowering this barrier to entry that discourages appropriately skilled but less well-funded teams from taking part would be not only setting minimum data standards, but also making the data freely available and easily accessible (queried via publicly available APIs).

The second enabler for scalability is speed of development – the “temporal” factor

85% of AI projects in general are estimated to deliver deficient results or end up restarting as data management projects, when teams discover that the data needed to achieve the original AI project’s goals does not exist or is not accessible as required.

Without dedicated funding, efforts to develop solutions will be sideshows to the principal activities of teams throughout organizations. The result is an agonizingly slow progress, with some projects ceding priority to others that generate income for the organization. Backburner projects are usually fragmented, staffed by many employees in their spare time or in gaps between other scheduled work. Lacking critical mass, collaboration and institutional memory can falter, resulting in unnecessary complexity in piecing together partial results, inevitable incompatibilities and subsequent rework. Achieving the goals set forth by this vision for AI-enabled wildfire risk management requires long-term focus.

The need for funding applies equally to procuring the hardware needed to process enormous quantities of data. Of course, ML models can be trained on laptops, running for days or even weeks. Assuming these underpowered computers don’t crash under the weight of the task, results are delivered in weekly or monthly increments. As all data scientists are aware, no complex ML projects deliver perfect results out of the gate. The strength of AI is its suitability to handle complexity; AI projects are inherently complex, otherwise simpler approaches would be accepted. That complexity – ranging from proper formulation of objective functions to data pre-processing, feature selection, exception handling, testing, all the way through to operationalization – makes iterations practically unavoidable. Having access to appropriate computing resources can reduce those increments from weeks to hours. Every year, the incidence of wildfires rises, as does their intensity. Therefore, in a race against time, shortening the iteration cycle is a key priority.

The third enabler for scaling is acceptance – the vital "human" factor

That means involving stakeholders up-front in the design of whatever solution – or bouquet of solutions – the technical team intends to implement. The human component is critical to success, both in order to ensure the result is useful (solving a relevant problem well) and to ensure that it is usable (accepted by its intended users). Without expert input, it is entirely conceivable that some data scientist teams might consider wildfire risk to be a purely weather-driven problem, ignoring the effects of geography and human behaviour. Without expert input, it is equally likely that these teams would produce a technical wonder that beautifully solves the wrong problem, or that can be operated only by the technical team… and that is ultimately never used.

Finally, the right technical infrastructure is the bedrock for a successful project

The technical infrastructure includes factors such as the future-oriented implementation and permanent availability of the solution. Data preparation and model development are better performed on scalable, managed cloud environments than on individual machines. Automatic backups reduce the risk of work being lost. Collaborative features speed up the progress of teams and reduce continuity risk as teams and organizations evolve. Furthermore, the cloud also offers the advantage that the capacities of computing power and storage capacity can be increased flexibly and automatically as the computing volume grows. The cloud is also the ideal platform to host the finished application, providing reliable access around the clock and centrally managing the periodic updates of the AI models on the latest available data.

5 A call to action

Governments, the private sector, academia and international organizations need to act on their strengths and expertise, supporting each other to find impactful solutions for fighting wildfires.

Effective wildfire risk management is hard – it always has been, and it is only getting tougher as firefighters worldwide wrestle with the uncertainties brought about by a changing climate. Firefighting is exhausting and dangerous work, made worse by the increasing incidence of wildfires year after year. Yet fighting wildfires is a vital defensive measure in combating global warming. Managing wildfire risk delivers immediate results. Doing otherwise is to acquiesce in the tragic destruction of natural habitats, valuable carbon sinks, lives and livelihoods – destruction that can take generations to recover, if at all.

Governments have it in their power to make a positive impact. They need not have all the answers, but by supporting experts and developer teams well positioned to help, they will arrive at the best results. This is no easy task, as they must balance ecological benefits and security with fiscal responsibility to taxpayers. Yet the stakes are too great for it to be a question of "if" rather than "how". It is true that responsibility does not rest only on the shoulders of the state, but the reality is that only governments possess the clout needed to put most of the necessary measures in motion.

Up until now, thinking about wildfires – and other disasters – has often revolved around relief for those affected, helping citizens in need. Ex post measures will never match the return on investment of ex ante, preventative measures. How can this be achieved? Citizens worldwide, confronted with dramatic images of raging fires on their screens, are sensitized to the urgency. Winston Churchill's adage "never waste a good crisis" was never truer than it is today. The time to act is now. And what shape might such actions take?

1. **Empower ministries:** Give ministers the mandate to work actively with experts to modernize their arsenal of weapons in the fight against wildfires – and other natural disasters. The stakeholders and project managers who are most familiar with the problem can share their requests for support with the ministries.

2. **Strengthen collaboration:** Academia, international organizations and the private and public sectors have different strengths. The private sector's solid technical expertise combined with the public sector's experience in the field may offer long-lasting and robust solutions in firefighting. The technical expertise of the private sector heavily depends on developments in academic studies. Finally, international organizations and NGOs facilitate cooperation among the players and help raise awareness.

3. **Incentivize contribution:** Voluntary contributions are welcome, but they can at best supplement a core, focused effort. International and national efforts are required to encourage coalitions of experts – scientists, tech providers, cloud providers and ML engineers/consultants – to work on this problem. While many are eager to dedicate time to making the world a better place, they must balance it with other priorities. Just as companies compete to attract talent, governments must compete with other projects to attract companies, universities and other organizations to work on the problem of wildfires. Engagements, grants, tax incentives – all financial tools can play a role.

There are subproblems in the wildfire space that it is not cost-effective for a single private entity to tackle.

4. **Prepare for a long-term effort.** Problems of this scale are complex. There may well be few meaningful quick hits. That does not automatically equate to only long-term goals – quite the opposite: projects such as these must be broken down into smaller parts with shorter deadlines, run in the same agile fashion as similarly complex projects in commercial ventures. Copious funding with unclear objectives and distant deadlines would only discourage productivity and detract from the sense of urgency. Spend, but spend wisely.

5. **Keep communication channels open.** Long-term projects require frequent broadcasts to the public and other stakeholders to generate enthusiasm (for interim results), ward off criticism (on spending) and encourage all to play a role. Initiatives seen favourably in the public eye will percolate into corporate agendas, opening up a willingness to contribute. Communicate the success – transparently to voters, to taxpayers – so that they remember the scale of the disasters before having implemented these new tools and techniques.

6. **Learn from open source:** The open-source community has been a lightning rod for innovation in data science, with universities and large organizations making their methods, frameworks, data and other technology publicly available simply for the prestige. Stakeholders can learn from this, establishing a similar open source-styled platform for data and data services.

7. **Work with international institutions:** This will encourage international public-private partnerships and provide free access to relevant geographic and weather data, consistently meeting minimum quality and granularity standards across regions. Co-invest internationally with hardware providers to establish sandboxes that give teams with promising ideas the computational resources they need – both high-performance computing to train models and cloud space to host models for demonstration purposes. This will lower the barriers to entry for teams of data scientists around the world who want to play a role. There are subproblems in the wildfire space that it is not cost-effective for a single private entity to tackle – for example, recording accurate wind forecasts and the like – which are areas that can be taken up by international coalitions.

8. **Volunteer to pilot:** Government volunteers should pilot and test AI models and new applications in different regions, provide resourcing and funding to encourage the sharing of wildfire data with other entities working on this problem.

9. **Contribute technical expertise:** Institutions and individuals with experience in the processing and handling of weather data, satellite data, data science and fire management can provide the technical expertise to develop applications. Cloud service providers can host these developed applications and can provide easy access to new data sources through APIs at local, national and international levels.

Conclusion

Wildfire risk management is a monumental task. It is not as simple as "fighting fires", but rather relies on "managing fires" – controlled burns are an effective tool used by firefighters to prevent and contain wildfires. Prediction is also fiendishly complex: it is not a "weather problem" alone, although weather and climate change play a substantial role. There are many challenges, from the availability of data to computational resource requirements. Another major setback is the scale of the endeavour, discouraging talent pools from getting involved once they appreciate its magnitude.

Despite all of the challenges, the case remains strong for enhancing wildfire risk management through the creative application of data, AI, high-performance computing and the cloud. Wildfires leave a trail of devastation behind them – affecting lives, livelihoods and valuable natural resources. What is lost in days can take generations to recover. The increasing incidence of wildfires is undeniably both a consequence of and a contributor to the environmental burden of global warming that harms nature and people alike, limiting access to fresh water and food, disrupting ecosystems and displacing populations. While a vision of automated AI-powered stewardship of Earth's precious environment once lay in the distant future, the technology is available today to turn the tables, to break out of the vicious wildfire cycle.

Useful wildfire risk-management solutions will not magically materialize from technology alone. Success requires dedicated efforts over the long term, with an expectation of many iterations of progressively better tools. Everyone has a role to play. Wildfires, like environmental protection overall, are not someone else's problem.

Governments can enable their ministries to take a more active role and empower them with the budget and decision-making power to do so. While they alone do not bear all responsibility, they can undeniably create the incentives needed for more active participation from highly qualified talent pools in academia and industry. They can listen to those already wrestling with the problem, putting their concerns on the agenda. International institutions such as the World Economic Forum can coordinate globally, to systematically address known issues, such as minimum quality standards, availability and free access to relevant data.

United by a clear vision, corporations can pitch in to help, sharing some of the burden with taxpayers, but also be rewarded for their contributions, whereas their competitors may have chosen to focus their resources only on profit generation. Organizations must be ready and willing to work openly with one another. This is too complex a problem for it to be solved without coalitions of experts, dedicated to working together in an equitable fashion.

Wildfires have become a problem on a global scale that demands global attention and coordinated action. The landscape is uneven; developed countries have more sophisticated tools at their disposal, both for planning and execution. By far the majority of the academic and commercial work being done to tackle this problem is aimed at developed countries, yet wildfires, especially in the context of their detrimental effects on the climate, are a worldwide problem. Developing countries are often at a disadvantage – lacking data and access to tools (the tools may exist, but may not be provided free of charge to fire departments). Addressing these needs would enable developing countries to improve wildfire management programmes locally.

The Deloitte and KoçDigital projects on wildfire risk management are an encouraging start. They provide some immediate value to their constituents. More importantly, they demonstrate that significant progress is possible today. The authors of this thank their readers for their attention and encourage them to join them in their efforts to combat this enormous climate risk to the planet.

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1. World Economic Forum, 2023. “The Global Risks Report 2023: 18th Edition”: https://www3.weforum.org/docs/WEF_Global_Risks_Report_2023.pdf.
2. National Interagency Fire Center, 2022. “Total Wildland Fires and Acres (1983–2021)”: https://www.nifc.gov/fire-information/statistics/wildfires.
3. Gabbert, B., 27 February 2021. “Updated: South Africa Wildfire Grows to More Than 33,000 Acres”, Wildfire Today: https://wildfiretoday.com/2021/02/27/two-firefighters-injured-in-south-africa-wildfire/#:~:text=Over%20the%20last%20week%20the,km%20east%20of%20Cape%20Town.
4. Redfern, G. and Morton, A., 28 July 2020. “Almost 3 Billion Animals Affected by Australian Bushfires, Report Shows”, The Guardian: https://www.theguardian.com/environment/2020/jul/28/almost-3-billion-animals-affected-by-australian-megafires-report-shows-aoe.
5. European Environment Agency, 18 November 2021. “Forest Fires in Europe”: https://www.eea.europa.eu/ims/forest-fires-in-europe.
6. World Meteorological Organization, 23 February 2022. “Number of Wildfires Forecast to Rise by 50% by 2100”: https://public.wmo.int/en/media/news/number-of-wildfires-forecast-rise-50-2100#:~:text=There%20is%20projected%20to%20be,the%20end%20of%20the%20century.
7. Copernicus, 23 January 2020. “OBSERVER: Unprecedented Australian Bushfires and the Copernicus Services”: https://www.copernicus.eu/en/news/news/observer-unprecedented-australian-bushfires-and-copernicus-services.
8. IPCC, 2022. “Climate Change 2022: Mitigation of Climate Change”: https://report.ipcc.ch/ar6/wg3/IPCC_AR6_WGIII_Full_Report.pdf.
9. US Environmental Protection Agency, July 2022. “Climate Change Indicators: Wildfires”: https://www.epa.gov/climate-indicators/climate-change-indicators-wildfires.
10. European Environment Agency, 18 November 2021. “Forest Fires in Europe”: https://www.eea.europa.eu/ims/forest-fires-in-europe.
11. Hoover, K. and Hanson, A. L., 4 November 2022. “Wildfire Statistics”, Congressional Research Service: https://sgp.fas.org/crs/misc/IF10244.pdf.
12. IPCC, 2022. “Climate Change 2022: Mitigation of Climate Change”: https://report.ipcc.ch/ar6/wg3/IPCC_AR6_WGIII_Full_Report.pdf.
13. Garthwaite, J., 22 September 2022. “Stanford Researchers Find Wildfire Smoke Is Unravelling Decades of Air Quality Gains, Exposing Millions of Americans to Extreme Pollution Levels”, Stanford News: https://news.stanford.edu/2022/09/22/wildfire-smoke-unraveling-decades-air-quality-gains/.
14. California Water Science Center, 5 June 2018. “Water Quality after a Wildfire”, USGS: https://www.usgs.gov/centers/california-water-science-center/science/water-quality-after-wildfire.
15. Morrison, R., 18 August 2022. “The Environmental Impact of Wildfires”, EARTH.ORG: https://earth.org/environmental-impact-of-wildfires/.
16. Li, S. and Banerjee, T., 22 April 2021. “Spatial and Temporal Pattern of Wildfires in California from 2000 to 2019”, Scientific Reports 11, 8779: https://www.nature.com/articles/s41598-021-88131-9.
17. Halofsky, J. E., Peterson, D. L. and Harvey, B. J., 27 January 2020. “Changing Wildfire, Changing Forests: The Effects of Climate Change on Fire Regimes and Vegetation in the Pacific Northwest, USA”, Fire Ecology 16, 4: https://fireecology.springeropen.com/articles/10.1186/s42408-019-0062-8.
18. Cagle, S., 4 September 2019. “‘Dragon’ Drones: The Flame Throwers Fighting Wildfires with Fire”, The Guardian: https://www.theguardian.com/us-news/2019/sep/03/wildfires-drones-controlled-prescribed-burns.
19. Goodbody, T. and Coops, N., 28 October 2019. “Drones Help Track Wildfires, Count Wildlife and Map Plants”, The Conversation: https://theconversation.com/drones-help-track-wildfires-count-wildlife-and-map-plants-125115.
20. DRYAD, 2022. “Silvanet Wildfire Sensor: Solar-Powered Sensor for Ultra-Early Detection of Wildfires”: https://www.dryad.net/wildfiresensor#:~:text=The%20Silvanet%20Wildfire%20Sensor%20is,temperature%2C%20humidity%20and%20air%20pressure.
21. Huang, H., Downey, A. and Bakos, J., 28 April 2022. “Audio-Based Wildfire Detection on Embedded System”, Electronics 11 (9), Scholar Commons: https://scholarcommons.sc.edu/cgi/viewcontent.cgi?article=1821&context=emec_facpub.
22. Newman, K., 8 November 2019. “A Waze for Wildfires: Learn How Tech Is Enabling Better, Earlier Wildfire Detection”, Ideas.Ted.Com: https://ideas.ted.com/a-waze-for-wildfires-learn-how-tech-is-enabling-better-earlier-wildfire-detection/.
23. Natural Resources Canada, 2022. “Background Information: Canadian Forest Fire Weather Index (FWI) System”, Government of Canada: https://cwfis.cfs.nrcan.gc.ca/background/summary/fwi.
24. Venäläinen, A. K. et al., 2014. “Temporal Variations and Change in Forest Fire Danger in Europe for 1960–2012”, Natural Hazards and Earth System Sciences 14, 6:, pp. 1477–1490: https://nhess.copernicus.org/articles/14/1477/2014/.

25. Rothermel, R. C., 1972. "A Mathematical Model for Predicting Fire Spread in Wildland Fuels", USDA Forest Service: https://www.fs.usda.gov/research/treesearch/32533.

26. Pagnini, G. et al., 2018. "Wildfire Propagation Modelling", Basque Center for Applied Mathematics (BCAM): https://www.academia.edu/77781713/Wildfire_propagation_modelling.

27. Keck, A., 16 September 2022. "Monitoring Fires with Fast-Acting Data", NASA: https://appliedsciences.nasa.gov/our-impact/story/monitoring-fires-fast-acting-data.

28. Earthdata, 29 January 2021. "NASA, Forest Service Partnership Expands Active Fire Mapping Capabilities": https://www.earthdata.nasa.gov/news/usfs-firms-us-canada.

29. Sullivan, B. K. and Del Giudice, V., 13 May 2022. "How Climate Change Is Fueling More Intense Global Wildfires", Bloomberg UK: https://www.bloomberg.com/news/articles/2022-05-13/how-climate-change-fuels-wildfires-billions-in-damages?leadSource=uverify%20wall.

30. World Economic Forum, "FireAId: AI to Predict and Fight Wildfires": https://www.weforum.org/projects/fireaid-ai-to-predict-and-fight-wildfires.

31. Huang, J., 12 November 2021. "NVIDIA to Build Earth-2 Supercomputer to See Our Future", NVDIA: https://blogs.nvidia.com/blog/2021/11/12/earth-2-supercomputer/.

32. Sønder, C. K. et al., 30 March 2020. "MetNet: A Neutral Weather Model for Precipitation Forecasting", Google Research: https://arxiv.org/pdf/2003.12140.pdf.

33. Pathak, J. et al., 22 February 2022. "FourCastNet: A Global Data-Driven High-Resolution Weather Model Using Adaptive Fourier Neural Operators", arXiv: https://arxiv.org/abs/2202.11214.

34. Guibas, J. et al., 24 November 2021. "Adaptive Fourier Neural Operators: Efficient Token Mixers for Transformers", Cornell University, arXiv: https://arxiv.org/abs/2111.13587.

35. Pathak, J. et al., 22 February 2022. "FourCastNet: A Global Data-Driven High-Resolution Weather Model Using Adaptive Fourier Neural Operators", arXiv: https://arxiv.org/abs/2202.11214.

36. Ibid.

37. WWF, 2019. "The Mediterranean Burns": https://awsassets.panda.org/downloads/wwf__the_mediterranean_burns_2019_eng_final.pdf.

38. Orman Genel Müdürlüğü, 2021. "Resmi İstatistikler" (in Turkish): https://www.ogm.gov.tr/tr/e-kutuphane/resmi-istatistikler.

39. Ibid.

40. "Stand map" is a term used in forest engineering to refer to a map that shows characteristics of the forest.

41. Van Den Meulen, R. and McCall, T., 13 February 2018. "Gartner Says Nearly Half of CIOs Are Planning to Deploy Artificial Intelligence", Gartner: https://www.gartner.com/en/newsroom/press-releases/2018-02-13-gartner-says-nearly-half-of-cios-are-planning-to-deploy-artificial-intelligence.

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