# Fighting Fire with AI

## Wildfires are a growing problem, their flames fanned by global warming

## Introduction

Wildfires—a terrifying, but by no means a new phenomenon—have become more commonplace, escaping an environmental equilibrium and exacerbating the very conditions that give rise to their frequency and severity. The Californian wildfires of 2020 released 91 million metric tons of the greenhouse gas $CO_2$ into the atmosphere, considerable against the global $CO_2$ absorption capacity of forests estimated at 7.6 billion metric tons annually.[1] The damage that ensues is substantial and enduring—what is lost in days can take generations to recover. Besides their longer-term environmental consequences, wildfires lay waste to natural resources, and can harm or tragically end the lives of residents and those who risk life and limb to bring the inferno under control.

Forecasting wildfires has been a focus of research for decades, but their growth in number and size demands more attention and better tools to tackle this environmental issue. The FireAId initiative, spearheaded by the World Economic Forum (WEF), aims to address one of the opportunities in fighting wildland fires through the use of artificial intelligence (AI) to help those fighting fires better predict where fire could start and how active fires may spread.

Deloitte and Nvidia have collaborated on this initiative, studying global fire history and trends, speaking with numerous firefighters, analyzing data and selecting the appropriate technologies to build and pilot tools to help firefighters tackle the escalation in wildfires.


## A moving target

Climate change is contributing to both the incidence and the intensity of wildfires, which makes predicting them ever more of a challenge. Rising temperatures have affected weather patterns, diminishing natural defenses, such as regular rainfall and rivers flowing from snow-capped mountains. Drier ground soil, grasslands and forests provide prime conditions for wildfires to ignite and propagate. Changes to terrain and weather diminish predictive power of historical data, placing the world in unfamiliar territory where hard-earned experience and intuition may no longer work as reliably as before. Well aware of this, environmental authorities around the world do account for ambient conditions in their fire risk metrics. Buildup Indexes (BUI) focus on "fuel," the combustible organic matter in vulnerable forests and shrublands. The Initial Spread Index (ISI) complements BUI by integrating the effects of wind. BUI and ISI are relevant to both risk of wildfire outbreak and the rate by which existing fires spread. Their collective effect is captured in the Canadian Fire Weather Index (FWI), which combines three fuel moisture codes alongside three fire behavior indices, and is updated daily on readings of temperature, wind speed, relative humidity, and precipitation.[2]

The metrics paint a worrying picture. FWI has risen consistently for 50 years.[3] The past 18 years have seen the most extensive damage.[4] There have been approximately 1.5 million wildfires since 2000, of which 237 burned over 100,000 acres and 15 over 500,000 acres. Since 2000, an average of 7 million acres have burned annually versus 3.3 million in the prior decade.[5] Fire danger zones are expected to nearly double under 3 °C global warming scenarios in European countries most affected by forest fires.[6]

Firefighters face are likely facing an uphill battle—drier vegetation is quicker to ignite, defying experience-based forecasting and putting resources and budgets under pressure. Timely response is critical, as is selection of the right intervention measure. This has motivated research and commercial offerings over the past decades, much of which rooted in the seminal work of Richard C. Rothermel in 1972 performed for the USDA Forestry Service.[7] His studies of wildfire were the first to quantify the importance of "fuel," the combustible living or dead material in the path of a fire, such as grasslands or forests. Rothermel categorized differing burn characteristics among fuel types—grasslands, shrublands, forests, down to different species of tree—as well as the density of foliage and moisture in the ground soil. His research also captured details, such as the effect of sparks swept into the fiery updraft, later descending on nearby vegetation and advancing the fire-front across barriers such as roads. The focus on fuel was a paradigm shift away from viewing wildfire as being driven mostly by momentary weather conditions.

The resulting mathematical models have been a foundation for further research ever since, as well as the governing equations behind wildfire forecasting software. Most prediction tools focus on forecasting the *spread* of fires that have already ignited. They are also limited in their forecasting accuracy. This new effort aspires to harness advances in technology, notably in AI and high-performance computing, to improve upon the models derived by Rothermel and those who followed in his footsteps.

## How to forecast a fire

**Wildfire forecasting has both a geospatial and temporal dimension. Any applied AI method must be well adapted to predict along both of those dimensions. Algorithms built to solve other, generally similar problems provide a good starting point. Geospatial can be seen as a computer vision problem, temporal as a time-series forecasting problem. Examples such as autonomous driving and weather prediction contain both dimensions, opening new opportunities for wildfire prediction.**

Key questions should be answered before delving into the tech itself: What are the exact prediction goals? What is the scope? Limiting to "active-fire" (spread) alone would potentially overlook vital preparation time. Settling on "pre-fire" (outbreak) would risk distracting firefighters with too many possibilities. How precise must the forecasts be in order to improve over traditional techniques? What is the forecast horizon? Greater accuracy may be achievable, if limited to 24 hours, but may inadvertently deprive firefighters of relevant information beyond that horizon. Even if longer-range forecasts become less precise, they may nonetheless have value.

Questions as these illustrate how wildfire risk management requires a collection of predictions. In order to target each forecast horizon individually, the Deloitte strategy for managing the risk of wildfire comprises three forecasting aims—three distinct problems:

1. The probability of wildfire outbreak – **the "pre-fire" problem**
2. The predicted velocity (trajectory and speed) of wildfire spread – **the "active-fire" problem**
3. The expected reaction of wildfire to intervention measures – **the "response" problem**

"Pre-fire" and "active-fire" are two very different problems, influenced only in part by the same factors. The "pre-fire" problem of wildfire outbreak is driven by a combination of weather conditions, ground conditions, and human activity. Worthy of note: most wildfires trace their origins to human activity, up to 85% in the United States,[8] including unextinguished cigarettes, campfires, faulty power lines, or other causes. The "active-fire" problem of wildfire propagation not only depends on weather and fuel, but also on topographical features such as incline of the terrain and—barring firefighting measures— much less on human activity. The two problems differ not only in feature importance, but in the very nature of the problem.

There is an aspect of randomness with the "pre-fire" outbreak problem that limits predictability to any of number of potential zones where fuel could ignite, rather than pinpointing exactly which of those zones will result in a wildfire. The risk of outbreak in one zone depends mostly on conditions within its boundaries, as ignition transferred from neighboring zones could be the propagation problem. This dynamic would seemingly allow reducing outbreak prediction to only a temporal problem, given perfect information for each zone. The reality from combining weather, fuel, topographical, and human activity data is that information is far from perfect or even uniform, giving greater relevance to information from neighboring zones.

The "active-fire" problem of predicting potential propagation pathways is inherently dependent on information from neighboring zones. While there continues to be an element of randomness, it is unlike that of the "pre-fire" problem since fire has already ignited. Propagation can be reasonably modeled more deterministically combining the pattern-recognition components of a spatio-temporal model with known physical dynamics. For these reasons, any useful forecasting model for either "pre-fire" or "active-fire" will necessarily address both temporal and spatial context, requiring a more sophisticated architecture.

Sometimes features may have an inverse effect on outbreak or spread. Roads, for example, are a proxy for human activity, positively correlated with outbreak. However, they may be negatively correlated with spread of fire, acting as a barrier to an advancing fire-front. Other examples include population density and biomass. Up to a point, population density may imply more risk of humans causing fire. After a certain density, however, we can safely presume an asphalted urban area: fires will still occur, but not wildfire. The duality also exists for biomass, an indicator for fuel. Dry biomass is highly combustible and a good risk indicator for fire. Wet biomass may impede the ignition and advance of wildfire. These are examples of the non-linearity of the wildfire prediction problem and why historical approaches have enjoyed limited success. Properly accounting for all the inputs, their (non-linear) correlations to prediction targets, and their inter-relationships is a complicated and computationally intense undertaking. It is fertile ground for shortcut patterns found by AI.

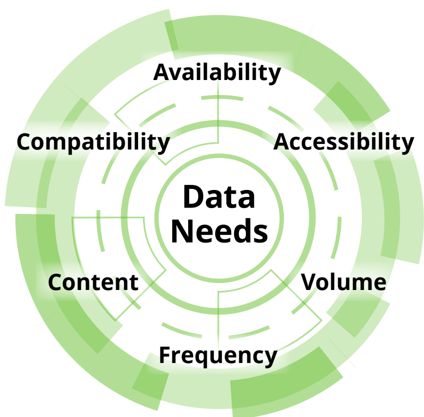
## Modeling challenges

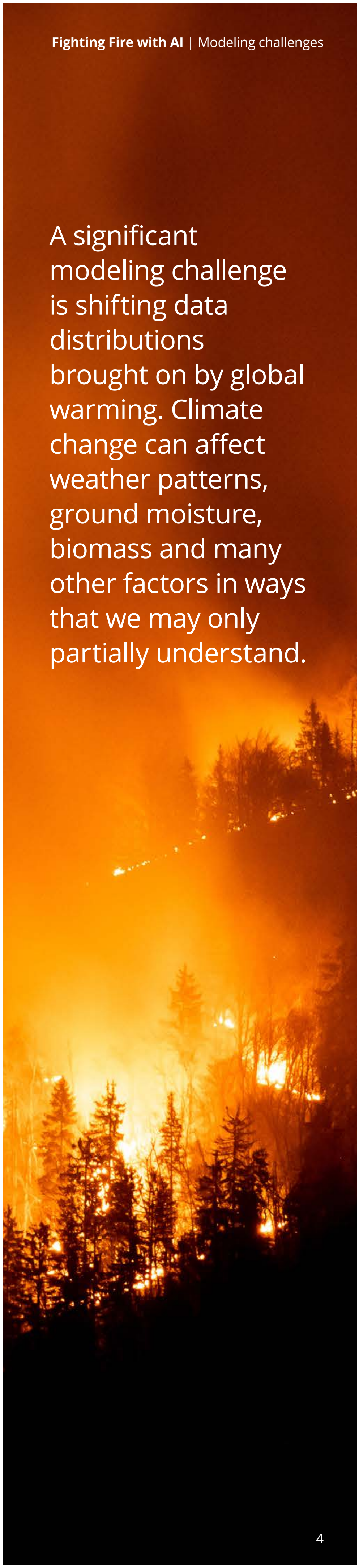
As is typical for problems addressed with AI, we are dealing with probabilities and not certainties. Beyond mere random noise variation, there is a complexity of external factors along both the geospatial and temporal dimensions that we can, at best, estimate as random. These are particularly acute as relates to the "pre-fire" problem: when and where exactly lightening may strike, or which hikers may not properly put out a cigarette along which part of their journey. The "active-fire" problem is not entirely immune to unpredictable external factors, but we estimate that modellable factors carry sufficient weight to govern most of the behavior of wildfire *propagation*. For predicting the outbreak of wildfire, we must be content with providing a heat map of probabilities across the entire geographic region under consideration which reflects ignition conditions.

A significant modeling challenge is shifting data distributions brought on by global warming. Climate change can affect weather patterns, ground moisture, biomass and many other factors in ways that we may only partially understand. We may nevertheless safely assume that wildfires will become more commonplace and more ferocious against a backdrop of higher temperatures and drier fuel. This poses a risk to machine learning (ML) prediction approaches, namely, that data on which models are trained may soon no longer be representative of data that the model will encounter in operation, significantly impeding the model's predictive power. A model that predicts how wildfires *used to behave* is of little use to firefighters. It is therefore tantamount to reliable ML models to ensure training data is not only representative at the time of training but also into the future. An effective measure to help manage this robustness risk is frequent re-training, essentially re-calibration, one of the core tenets of machine learning operations (MLOps).

Another challenge lies in balancing relevance versus overfitting: generalization of a model beyond its training data is critical for success. (Overfitting: a model perfectly correlated to its training data will effectively only be able to predict the training set and—often spectacularly—fail when attempting to predict on new input data.) This principal raises a central design question of balancing model complexity, accuracy and efficiency: for instance, whether a single large model or multiple, dedicated models (such as per geography) would enjoy higher predictive power. To what degree can models learn from a larger pool of data, full of multi-dimensional patterns? Or do large models simply become untenable, beleaguered by complexity needed to weight features differently depending on other features, capturing the intricate combinations from one geographical region to another?

Arguably, the most crucial ingredient to building effective AI models is the data. To even warrant an AI approach, a sufficient *quantity* of data is required—a broad selection of features and a sufficiently long history of records. This data needs to be representative and of an adequate *quality* – grounded in accurate and complete readings. Given the "nowcasting" immediacy of the forecasting problem, the data is required in a timely, frequently updated fashion: the temporal dimension. To provide useful guidance, the data must be available in reasonable granularity or resolution: the geospatial dimension. Equally important considerations are accessibility, procurement cost, and ease of processing (e.g., size, formats, and metadata).



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But first, which variables (features) do we need for prediction? Taking inspiration from Rothermel, data needs have been roughly divided into three categories:

- **Topography** – static features of terrain, altitude, inclines, natural landmarks such as lakes, rivers, mountaintops, and man-made landmarks such as hiking paths, roads and powerlines. (Man-made landmarks are also effectively a proxy for human activity, a key component for the "pre-fire" problem of wildfire outbreak.)
- **Fuel** – gradually evolving features of surface conditions such as moisture of the soil, density and types of vegetation
- **Weather** – often volatile conditions in the air and lower atmosphere such as temperatures, wind speeds, precipitation and humidity

Topographical data are basically static over time: the corresponding satellite images need only be updated annually. Raw satellite images could also be used to gauge fuel conditions: Sentinel-2 captures spectral frequencies suitable for estimating biomass and thus the presence and combustibility of fuel. Dynamic data sources represent a greater challenge, which may vary in "shape" (e.g., breadth of features, granularities, and update intervals). The data pipeline and repository are flexibly structured to accommodate these eventualities. Data volumes from frequently updated sources can quickly get out of hand, particularly for "bulky" sources such as raw satellite images. They can also be expensive to source in a useful form: while ESA's Sentinel 1 and 2 images are available to the public, in practice, stitching them together may only be feasible through non-free application programming interfaces (APIs) that provide the necessary coordinates. Procurement, processing, and storage costs would become a substantial factor at the geographic scope of wildfire forecasting.

Sentinel 1 and 2 are also limited in spatial resolution (10 m²) and frequency (between them every 5 days). More granular sources are available, but expensive: 3 m² resolution at daily intervals costs roughly US$20,000 per year for 100 km² coverage. Wildfire prediction would likely require 10-50 times that coverage to be effective. Free versions are not an option (beyond use for static topographical data) due to the sporadic update frequency. Custom data sources such as drones could provide a dramatically higher geospatial and temporal resolution to collect wildfire *propagation* data in selected areas, but this would likely require a dedicated investment into hardware and their operation. Unmanned aerial vehicles (UAVs) are already in use in some countries. Not only can they provide close-range reconnaissance without endangering firefighters, they can also play an active role in fire defense, by igniting pre-emptive controlled burns to starve a wildfire of fuel in a particular pathway.[9] Some forests are even equipped with advanced smoke detectors.[10] Experiments are also underway to extend sensing capabilities using microphones and algorithms attuned to the crackly sounds of fire and of wildlife reacting to fire.[11]

As fire departments frequently emphasized, the *timeliness* of data is of critical importance to fighting fires. Building a useful wildfire forecasting tool with AI would require a rich dataset over a long period of time that is updated several times a day. We were not able to find any dataset that satisfies those criteria. Satellite data, in addition to its "bulkiness," is generally updated too infrequently to be of practical use to the short-term requirements of wildfire forecasting. Weather data provides a more compact alternative, much of it derived from satellite images, but pre-processed and reduced to specific features in which users are interested. Of the many other datasets researched, two weather datasets complemented each other well, providing a practical way forward:

- **NOAA** (National Oceanic and Atmospheric Administration) – contains both actual weather readings and historical forecasts, each updated several times a day. The downside: the NOAA dataset exists only since 2020. It is timely and well-suited to informing on risk of wildfire outbreak and spread, but lacks the history to train an AI model of the desired forecasting time horizon (7 days).
- **ERA5** – contains a wide set of features and dates back to 1959. The downside: it is updated only every 4-6 weeks and contains no forecast information. It is too infrequently updated to be of any use for fast-changing outbreak risks or advances of a fire-front, however it provides ample history to train a forecasting model.

The Deloitte approach maximizes the use of both datasets by splitting each prediction objective—outbreak and spread—into a two-stage problem:

1. Nowcasting the first 24 hours – using highly current information for greater reliability
2. Forecasting the 2nd to 7th day – using longer data histories for longer-term predictive power

Doing so would provide firefighters with both highly up-to-date information, as well as a view into the near-term potential development. Measured in weeks, NOAA's history amounts to a paltry 108 datapoints, hardly sufficient for a week-long forecast. However, NOAA's thrice daily actuals and forecasts over two years provided us nearly 5,000 datapoints—a decent foundation, and one that adds six new datapoints every day. Limiting the application of NOAA data to forecasting only the first 24 hours makes the dataset more viable. Leveraging both the historized actuals and forecasts provides an additional accuracy gauge. The ERA5 dataset, while coarse to nowcast the next 24 hours, could be applied to a less time-sensitive, longer-range forecast. Using the data from 1979 through 2015 would suffice to train a second forecasting model.

The nature of each of these distinct forecasting problems and the associated appropriate datasets demanded special attention to selection of the appropriate algorithm and model architecture.

- **MetNet2** – developed by Google for predicting rainfall and trained on the NOAA dataset, MetNet is particularly well suited to the spatio-temporal "propagation" problem. It has an unparalleled spatial resolution of 1 km², a degree of precision highly suited to the forecasting demands in geolocating an advancing fire-front.

- **FourCastNet2** – adaptive Fourier neural operators implemented in the physics-informed Modulus SDK by NVIDIA. The original was trained on ERA5 data to predict global weather, particularly extreme events such as hurricanes with a spatial resolution of 25 km². The adaptation for wildfire (version 2), also trained on ERA5, focuses on conditions for wildfire and aims for more precise resolution than the 25 km² of its predecessor, FourCastNet.

For both, the F1 score (alongside precision, recall and ROC) is the most appropriate optimization metric. F1 is the harmonic mean of precision and recall, where precision indicates the portion of predictions that were accurate (versus false alarms), while recall indicates the portion of accurate predictions over all cases that should have been predicted (total relevant results). The choice of metric is important to ensure the AI model optimizes toward the right goal. Accuracy, or correct predictions over all relevant results, is not a suitable metric, as the incidence of wildfire outbreak can still be considered an outlier event—not normally distributed, but rather a skewed distribution with a long tail. Concretely in the case of wildfire, precision shows how many wildfire predictions correspond to actual wildfires, where recall shows how well the model predicted all actual wildfires. Optimizing on "accuracy" would suggest the simplistic function "y = 0" to predict wildfire outbreak, which would be, on average, highly accurate, while failing to catch a single wildfire.

## From prediction model to risk management solution

Long-term, the predictions could provide the necessary input to guide a semi-autonomous wildfire risk management ecosystem comprised sensors and actuators. A combination of permanent sensors on the ground or up in tall trees, mobile phones, roving drones, and satellites could create a web to collect relevant information. A collection of AI models would make sense of this data, finding patterns with predictive power for both outbreak and spread of wildfires. If these prediction engines were sufficiently precise and reliable, they could automatically launch scenarios to test intervention strategies in a digital twin and ultimately trigger actuators of various kinds: sprinklers, targeted drone flights, autonomous vehicle fire trucks, and alerts sent to human firefighters. With enough foresight, some actions might even prevent wildfire outbreak rather than contain the fire—preventative maintenance for the forest. Autonomous AI systems are, however, significantly more complex and risks are greater when they fail. An application of autonomous AI to systems designed to provide safety are considered critical infrastructure and considered by regulation such as the EU AI Act as "high risk systems," requiring the utmost scrutiny and adherence to high-quality standards.

Wildfire risk management strategies generally fall into three categories: prevention, containment, and response. Prevention measures generally focus on issuing and enforcing rules governing human activity. Containment measures center around pruning forests with cleared corridors that would halt the progress of a runaway fire. Response measures comprise classical firefighting interventions, dousing flames from the air or from the ground. Cost factors differ widely per strategy. Enforcement measures cost little individually, however require widespread implementation year-round. Firefighting interventions are event-triggered yet demand substantial resources when they are enacted. Beyond budgetary concerns, downstream reactive strategies pose greater risk to lives, habitats and property. In manufacturing, repair costs climb exponentially the later a defect is found. The same holds true with wildfires: costs to manage them escalate the more expansive the fire-front becomes.

Whereas predicting outbreak and spread of wildfires can gain valuable preparation time, simulation can improve effectiveness of response. The ability to vet firefighting strategies in faster-than-real-time using a representative digital twin constitutes a technological upgrade compared with current planning capabilities. Questions about aerial or ground-based firefighting methods, optimal starting points, length and width of intervention activity, or the necessary amount of water or the flame retardant Phos-Chek could be evaluated before wasting time and resource on potentially hit-or-miss measures.

The usability of such a prediction and scenario simulation tool is nearly as important as its accuracy. Gaining control over wildfires is a race against the clock, not a calm environment to ponder possibilities. It is a raging battle against a foe who knows no indecision and needs no rest. Tools should be intuitive and intelligently designed to require as few keystrokes and clicks as possible for firefighters to immediately access the information they need. Anything less will result in tools that are not used, reverting to gut-feel methods of the past. After all, the best information, if delivered too late, is less useful than approximations available on time.


## FireAId first milestones

Deloitte's wildfire risk management solution uses a visual interface to evoke instant understanding and effortless data entry to accelerate the use of AI and simulation tools. Borrowing from concepts of virtual reality, it aims to serve as an extension to the firefighter's mind, at once both a canvas and a calculator on which to design, test and articulate optimum intervention measures when every second counts. This is greatly facilitated by the close alliance between Deloitte and NVIDIA, which provide both the high-performance GPU-hardware to train complex AI models, as well as the software, such as the Modulus software development kit (SDK) to complement data-shaped AI algorithms with known laws of physics. NVIDIA Omniverse integrates these multiple components and presents them in an interactive, visually compelling interface.

The Deloitte-NVIDIA solution was in mid-development at the time of the WEF publication. An encouraging start in this direction is made by another participant in the FireAId initiative. Koç Digital has piloted a project focused on the Turkish coastal region working closely with the Turkish Ministry of Agriculture and Forestry, which provided the data. Koç has constructed a first multi-variate prediction model for wildfire outbreak. Koç leveraged local data optimized for the region in their focus. The Deloitte approach leverages globally available data to maximize portability to other geographies.

Both the Deloitte and Koç teams are well aware that this effort will be an iterative journey, measured in months and even years. There are several significant barriers that stand in the way of developing and deploying effective wildfire risk management solutions:

- **Data barriers** – differing standards and availability, bulkiness of satellite data, costly APIs
- **AI/ML barriers** – the elements of randomness, non-linearity, and data sparsity prevent directly training a supervised model on "wildfire occurrence"
- **Computational barriers** – spatio-temporal model complexity requires powerful computing capabilities (GPUs)
- **Tech expertise barriers** – talent can be scarce, and it is often difficult to find staff for commercial projects, let alone dedicate staff to work on long-term, non-paying initiatives
- **Domain barriers** – expertise in AI alone will likely fail without involving experts, scientists in wildfire
- **Management barriers** – busy firefighters must invest some time to help shape the solution and must test the new tech versus traditional experience methods

## Conclusion

**Bringing wildfire under control is a difficult, dangerous and exhausting endeavor. Climate change is only making it harder. Firefighters play a critical role, not only in limiting the damage to life and resource felt locally and immediately, but also in slowing the long-term vicious cycle of wildfires themselves contributing to global warming. Unlike many other ecological measures, the benefits of effective wildfire management are felt immediately as well as over the longer term.**

The development of advanced tools to help fight wildfires, and combat the damage of climate change in general, is in the public's interest. Developing such tools is a major undertaking, and all stakeholders have a role to play:

- **Firefighters** must be involved in advancements to ensure usability of the tools. They are both "customer" and "co-creator," contributing extensive experience in fighting fires. Yet they lack the means, with more pressing funding concerns, such as replenishing aging equipment.
- **Governments** will be key in driving the agenda, mobilizing resources, setting data standards, and investing in hardware (e.g., sensors, data collection, and actuation). They must stay the course over the scope of activities and facilitate the international cooperation required to solve a problem of global scale.
- **Public-private partnerships** spearheaded by internationally cooperating government ministries combine the know-how with the authority to make a positive impact. The field requires innovation, where the private sector can take the lead. Where the profit motive drives innovation in private enterprise, it may not be necessary with wildfire. The desire to make a positive contribution, passion of individuals for the cause, marketing power for organizations will certainly play a role. However, mobilizing the private sector must at least cover costs if it is to be sustainable.

Leaders will likely be challenged articulating the need to balance short-term needs with long-term environmental security. It will be a long haul before we reach the stage of semi-autonomous wildfire risk management. The world is past the point where this can be a question of *whether* to invest into wildfire risk management—and sustainability in general—rather a question of *how* to best put scarce resources to work.

## Endnotes


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