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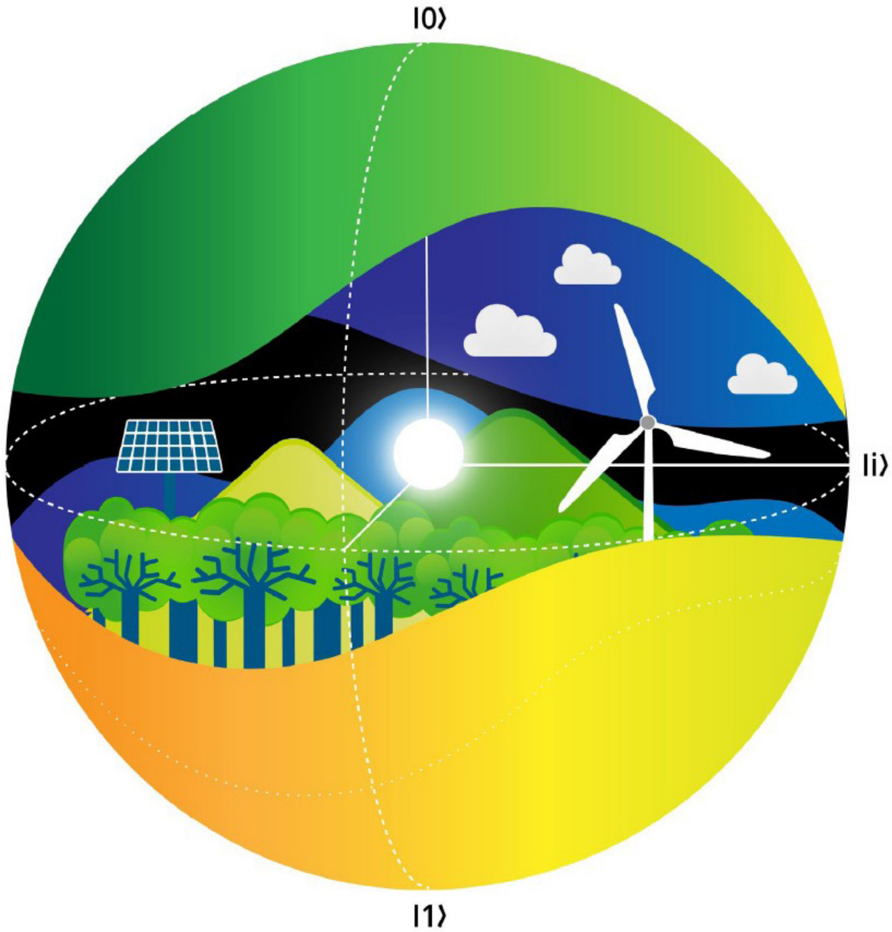

2026 Quantum Sustainability Challenge

Wildfire Risk and Insurance Premium Modeling

Overview & Goal of the Challenge

Deloitte's Quantum Sustainability Challenge for 2026 aims to explore the potential for Quantum Machine Learning (QML) technologies to help enhance wildfire risk modeling and improve insurance premium modeling for urban areas facing growing wildfire risks. Among many underlying forces, rising global temperatures and shifting weather patterns are driving more frequent and severe wildfires. According to the World Resources Institute, 2024 was the most extreme year on record for forest fires, surpassing the previous 2023 record by 13%.[1]

As the unpredictability and severity of wildfires rise, societies across the globe need to increasingly adapt to the profound financial impacts of these events on local and regional economies. One such economy, that of the State of California, is particularly susceptible to wildfires. California represents the fourth largest economy in the world, with an estimated Gross Domestic Product (GDP) of just under $4.1 trillion in 2024.[2] Yet, in the fall of 2024 in Los Angeles, one single fire season alone created over 8,000 wildfires in the region, destroying over 1 million acres of land. This translates to significant impacts on home owners and insurers in the region, underscoring the importance of improving modeling and prediction for wildfire risk assessments, and how these assessments translate into insurance premiums in fire sensitive regions both in California and globally.

[1] James MacCarthy, Jessica Richter, Sasha Tyukavina and Nancy Harris. World Resources Institute: The Latest Data Confirms: Forest Fires Are Getting Worse. Published July 21, 2025. Link: https://www.wri.org/insights/global-trends-forest-fires

[2] U.S. Bureau of Economic Analysis: Regional Data: Gross Domestic Product by State. Last modified September 26, 2025. Link: https://apps.bea.gov/iTable/?reqid=70&step=30&isuri=1&major_area=0&area=06000&year=2024&tableid=505&category=1505&area_type=0&year_end=-1&classification=naics&state=0&statistic=-1&yearbegin=-1&unit_of_measure=levels

[3] Cal Fire: 2024 Fire Season Incident Archive. Accessed 1/27/2026. Link: https://www.fire.ca.gov/incidents/2024

Advances in modeling and computation technologies can improve the prediction of wildfire risk. Small enhancements in the capability to predict wildfires using complex data which measures wildfire risk using many data sources can save lives, wildlife, and property. Specifically, Quantum Computing offers the potential to improve wildfire detection through QML algorithms. QML algorithms can improve insurance modeling in wildfire-prone regions, improving both private and state backed insurance programs to better serve the citizens and enterprises they represent.

Specifically, this competition presents participants with wildfire and insurance datasets for California zip-codes, and asks participants to apply quantum technologies to these datasets to solve a two-fold problem:

Task 1A: Create a quantum algorithm, a (hybrid) quantum machine learning model, that predicts the future risk of a wildfire occurring in California zip-codes in 2023, based on historical data (2018-2022) which are provided in the wildfire dataset.
To reduce complexity, a 'wildfire' will be defined by if it burns in a wildland setting and is unplanned and uncontrolled. Run your algorithm on a quantum computer or simulator and provide information on the resource requirements of your solution.

Task 1B: Evaluate your solution, describing the advantages and disadvantages of your approach(es). Evaluate the performance differences between your solution and classical approaches.

Task 2: Create a time series model to predict future insurance premiums in 2021 based on historical data (2018-2020) provided in the insurance dataset. Wildfire risk for each zip code is provided by the model output in Task 1 or use the existing fire risk score provided in the dataset.

Submission Format of the PDF File:

1. Overview of the individual or team and background(s) including your contact details (name, team name, e-mail, college or university affiliation).
2. ONE page summary/abstract of the participant's solution with a maximum of 400 words.
3. A detailed description of the participant's algorithm including the concept, general composition, underlying assumptions, and Evaluation. List all additional data that were used.
4. Description of results of the participant's algorithm and clickable link(s) to a repository that includes the code used to run the team's algorithm.
5. Description of the envisioned algorithm including the expected benefits and elaboration on the requirements for the solution.

Drivers Behind More Severe Wildfires in California .

To understand why more powerful and nuanced modeling technologies are needed for wildfire risk assessments, it is important to understand what is driving more frequent, unpredictable, and extreme wildfires in California. Multiple environmental and anthropogenic factors contribute to wildfires in California's ecosystems; however, a major contributor to the problem is rising temperatures. In California specifically, nine of the ten warmest years on record have occurred since 2014, with 2023 and 2024 setting records.[4] Ecosystems behave in feedback cycles, so when a fundamental variable induces a shock to an ecosystem such as higher average temperatures, it creates a cascading effect. In California, of the many down-stream effects of rising temperatures, droughts and fires are highly visible to society. Below represent examples of the cascading effects, or 'drivers' behind droughts and wildfires.

[4] State of California Office of Environmental Health Hazard Assessment: Air Temperatures. Published October 24, 2025. Link: https://oehha.ca.gov/climate-change/epic-2022/changes-climate/air-temperatures#:~:text=Statewide%20annual%20mean%20temperatures%20have,leading%20to%20exacerbated%20drought%20conditions.

Rising Temperatures and California's Water Cycle

California is home to a complex, fragile, and broad-spanning ecosystem representing 16 different climate zones—regions representing unique weather patterns and average temperatures. They include Mediterranean, desert, highland, steppe, tundra, alpine, and more. Many of these zones have resource interdependencies, and water is at the core, driven by the Orographic Effect.

The Orographic Effect is a natural system in California, in which moist air from the Pacific Ocean is pushed up mountain ranges such as the Sierra Nevada, and as the air rises, it cools and produces rainfall. During the winter months, historically, these mountain ranges store water en-masse through snow and ice buildup, resulting in spring and summer melting which feeds rivers that support the surrounding ecosystems.

However, higher average temperatures in California are resulting in faster and earlier snowmelt, meaning that drought cycles during dry months worsen, and the ecosystem becomes dryer and more arid. The data reflects it; California's OEHHA determined that the annual snowpack in the Sierra Nevada is consistently trending downward, and could result in snow-lines up to 1,600 feet higher by the end of the century, resulting in "severely challenged" long-term water management.[5] Such an effect creates elevated wildfire risk, as vegetation and brush become increasingly dry in warm seasons with elevated average temperatures.

Rising Volatility in Weather Accelerates Active Wildfire Spread

Californian droughts alone are one of multiple contributing factors to dangerous wildfires. Another factor, hydroclimate whiplash—the rapid shift between wet and dry conditions—is another leading contributor to the rise in wildfires. When heavier than usual precipitation occurs, more vegetation grows. When longer, drier seasons follow, the increased vegetation then dries out and serves as added dry brush for potential fires. The more hydroclimate whiplash occurs, the more exacerbated the cycle becomes.

A key phenomenon driving hydroclimate whiplash is an expanding atmospheric sponge, in which a warmer temperature enables the atmosphere to hold more moisture, leading to more evaporation during dry seasons, and precipitation during wet seasons. As California's climate continues to warm, its atmosphere will continue to absorb more water, driving more whiplash.

Beyond hydroclimate whiplash, other volatile weather conditions like winds can significantly worsen wildfires. Wind delivers oxygen that intensifies flames, further dries out vegetation, and pushes fires into brush areas unpredictably. In California specifically, Santa Ana winds in Los Angeles (LA) and Diablo winds in the Bay Area can reach extremely high speeds. These winds travel toward the coast and are drier and hotter than the moist wind that travels from the sea, making them prime to spread fires when coinciding with drought conditions.

Exceptional dryness and strong winds can be major factors behind the severity, speed, and expansiveness of wildfires in regions like LA. Santa Ana and Diablo are examples of natural weather events that, when coinciding with global warming induced phenomenon such as extreme droughts, can induce more acute wildfires with heavier societal costs, particularly to homeowners and home insurers with assets located in the disaster zone.

Improper Foresting Techniques and Lack of Controlled Burns

Modern land management has gradually developed techniques to manage the buildup of highly flammable brush in forests and national parks, but for many years, services did not deploy preventative techniques such as controlled burns that were historically practiced by indigenous groups.[6] This led to significant brush buildup in the 20th century and in turn, compounded as fuel for wildfires. Controlled burns are a wildfire prevention technique in which parts of a forest are identified and intentionally burned in a controlled setting to prevent shrubbery and other fuel from stockpiling and endangering human societies, and the broader ecosystem. Many forest service teams in California have adopted controlled burning over time and even require it as part of the fire cycle.

The Cumulative Impact: Less Predictable, Faster and Larger Wildfires in California

Global warming, more extreme water cycles, hydroclimate whiplash, volatile wind patterns, improper foresting techniques, urban development, and other factors are now converging to drive more extreme wildfires. Ecological and anthropogenic data are growing in both number of sources and data points for each source, presenting challenges to conventional methods of wildfire prediction as well as predictive machine learning models.

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[5] California Office of Environmental Health Hazard Assessment: Indicators of Climate Change in California. Accessed 1/27/2026. Link: https://oehha.ca.gov/sites/default/files/media/epic/downloads/ips_swc2018.pdf

[6] National Park Service: Indigenous Fire Practices Shape Our Land. Last Modified March 18, 2024. No claim to original U.S. Government works. Link: https://www.nps.gov/subjects/fire/indigenous-fire-practices-shape-our-land.htm

Current Approaches to Wildfire Prediction and Insurance Modeling

Understanding the drivers of wildfires and accurately forecasting them can allow residents and firefighters to prepare for, and even prevent, destructive wildfires. Forecasting is particularly critical to insurers. This entails identifying fire-prone regions, and the potential impacts of wildfires through scenario modeling. These models allow insurers to accurately price their products, and in turn, give fair and competitive rates to homeowners. When the variability of weather events rises, this creates additional risk for insurers, who then must budget that risk into higher premiums. Therefore, reducing uncertainty in turn reduces pricing risk, which helps drive more affordable rates for homeowners.

Data Acquisition

Insurers collect a wide array of data sources to capture the multifaceted nature of wildfire risk. This includes climatic and meteorological data (such as temperature, humidity, and drought indices) to assess weather-driven fire potential. Vegetation and fuel characteristics are gathered to determine the amount and flammability of material available to burn. Topographic information like elevation and slope helps model fire movement through landscapes. Anthropogenic factors (proximity to human settlements, ignition sources, historical fires) are integrated to understand human contributions to ignition and spread. Finally, remote sensing data from satellites (vegetation, fire hot spots, land cover changes) provide near-real-time context on landscape conditions.

Output and Application

Model outputs are translated into accessible formats—often risk maps—that show predicted risk levels across geographic regions. Insurers and fire agencies use these results to allocate resources more efficiently, such as pre-positioning firefighting teams in threatened areas. Early warning systems can be triggered based on heightened risk signals, notifying communities ahead of time. Insights can also inform prevention strategies, such as targeted vegetation management or public awareness efforts to reduce human-caused ignitions. Ultimately, these models enable proactive approaches to wildfire management and insurance risk mitigation, and the core technology driving many of these models is machine learning (ML).

How Machine Learning Works

Predictive ML

ML is a subfield of artificial intelligence (AI) that uses algorithms trained on datasets to create models. Unlike traditional programming, where a programmer defines explicit rules, ML models can perform tasks (semi)-autonomously that would otherwise only be possible for humans. Additionally, algorithms enable the system to learn and develop from given data to make decisions or predictions without being explicitly programmed to do so. Possible tasks could include categorizing images, predicting price fluctuations, and many more.

ML's ability to extract insights from large volumes of complex data and improve performance over time makes it a powerful tool in the modern technology landscape. At the core of ML are algorithms, which are sets of rules or instructions that the computer follows to process data and learn from it. These algorithms can be categorized broadly into three types:

1. Supervised learning, in which the algorithm is trained on a labeled dataset in which the data is already tagged with the correct answer or outcome. By example, a supervised learning ML model might be trained to recognize cats in photographs by being shown thousands of labeled images of cats and dogs.
2. Unsupervised learning, in which the data is not labeled, and the algorithm must find patterns and relationships on its own.
3. Reinforcement learning, in which the algorithm learns to achieve a goal in an uncertain, complex environment where it is rewarded or penalized for the outcome. By example, learning to play chess through continuous matches.

Quantum Machine Learning Can Help Manage Growing Complexity

As global warming accelerates, the variables influencing wildfire risk—such as temperature extremes, drought frequency, vegetation shifts, and human activity—are becoming increasingly volatile and unpredictable. QML combines quantum computing—a cutting-edge field using the unique properties of quantum physics—with traditional machine learning methods to process and analyze data features in new ways. In ML, a feature is any measurable property or input (think of spreadsheet column titles for temperature, wind speed, or distance from a road) that helps the model make predictions. As the number of features (or columns to analyze) grows, the data becomes more dimensional and harder to manage.

We believe that QML algorithms have the ability to potentially account for rapid, non-linear changes and the cascading uncertainties now seen across ecological and anthropogenic factors. Moreover, we believe that the high-degree of interconnectedness of wildfire risk variables complicates relationships between features, which shows promise for improvement through applying QML versus classical ML algorithms in an increasingly warming world.

Tying It All Back: The 2026 Challenge

Below, we have outlined the specific tasks and guidelines for the 2026 Challenge. Details on how to access AWS Braket and IBM's quantum computing resources, and the data on California regional wildfires can be found on the Resources tab of the challenge webpage. The details and data are only visible for registered participants of the challenge.

Once registered for the challenge, to successfully complete this challenge, we ask that you perform the following tasks:

CHALLENGE TASKS & SUBMISSION DETAILS

Task 1A: Create a quantum algorithm, a (hybrid) quantum machine learning model, that predicts the future risk of a wildfire occurring in California zip-codes in 2023, based on historical data (2018-2022) which are provided in the wildfire dataset.
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