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MEREDITH BRASELMAN: Ladies and gentlemen, good afternoon, and welcome to the U.S. Department of Energy Office of Electricity's fourth and final wildfire mitigation webinar. We are pleased to have all of you here with us today. We know that many of you have participated in the previous three webinars, and we thank you so much. I'm Meredith Braselman with ICF, and our team will guide you through the webinar today.

First, a few housekeeping items. We have muted your lines upon entry, and they will remain muted during the duration of the webinar. Please note that this WebEx call is being recorded and live streamed on DOE's YouTube channel. It will be posted on the Department of Energy's website and may also be used internally. If you do not wish to have your voice recorded, please do not speak during the call. If you do not wish to have your message recorded, please turn off your camera or participate by phone. If you speak during the call or use a video connection, you are presumed consent to recording and use of your voice or image. If you have technical issues or questions today, please type them in the chat box and send to our host.

We are going to start our discussion today with a quick poll. We'd like to know if prior to today's webinar, if you've ever talked to the Department of Energy or National Lab about technologies to help mitigate wildfires. So, please take a moment to answer that in the polling function.

While you're doing that, I will let you know that we are taking questions today. Please submit your questions throughout the presentations. But because we're going to hold them till the end, please also include the name of the presenter or the topic so that, at the end of the workshop today, we can direct them to the correct panelist.

And finally, if you need to view live captioning, please refer to the link that will appear in the chat panel.

DOE is honored today to have Senator Ron Wyden of Oregon to provide us with our opening remarks for the webinar. So, please join me in welcoming Senator Ron Wyden.

RON WYDEN: It's good to be able to talk about what is at stake with grid resiliency, especially during wildfires. To say this work is important is an understatement. It is lifesaving, especially in the West. In the last year, Oregonians got not one but two unwanted lessons on the dangers of a rundown power grid. We learned that when a winter ice storm hits, old power lines snap, and 450,000 people will be without power for days on end. No lights.

Last fall, Oregonians also saw that a once-in-a-century windstorm combined with record breaking heat means downed power lines that ignite wildfires so large and intense that nearly one quarter of the state's population was under evacuation orders.

Now, the climate crisis is not some threat in the distant future. It's here. We are living it. The climate is changing, which means upgrades to the power grid are long past due. That's why I recently introduced the Disaster Safe Power Grid Act. That's because it's important that steps are taken now to protect our electric infrastructure from calamity. The bill builds off a lot of the great work being done at the National Labs to strengthen wildfire mitigation capabilities.

It's also important to recognize the expense of these investments and make sure that our families aren't on the hook to cover all of the costs of the upgrades. For example, building underground power lines can cost upwards of four times more than overhead wires. This is a matter of public safety. And hard-working American families should not have to see a hike in their power bills to pay for the urgent safety fixes.

My legislation makes the federal government a partner to power companies in the private sector, incentivizing all of them to do more to reduce power blackouts and wild land fires, like strengthening utility poles and power lines, undergrounding equipment when possible, and clearing brush and hazard trees. This can add up to a modest cost to the public, but an ounce of prevention in this case is worth tons in community safety. And with the Department of Energy at work with respect to cutting-edge research, I'm absolutely certain that these lifesaving improvements are possible now and will be even more innovative in the years ahead.

MEREDITH BRASELMAN: Thank you so much, Senator Wyden, and to his staff for joining us today and providing his support on this very important topic.

So, now it's time to hear from our colleagues at the National Labs. Today, we're going to hear from Xiaoyuan Fan, Mark Wigmosta, Andre Coleman, and David Judi from Pacific Northwest National Laboratory; Qing Zhu, Robinson Negron-Juarez, David Romps, William Riley, and Bin Wang, from Lawrence Berkeley National Laboratory.

As a reminder, you're welcome to submit your questions in the chat box. Please send to our host. We're going to hold all of our questions until everyone has spoken. So, when you submit your questions, please do include the name of the speaker or the topic so that we can address them to the right person at the end of the presentations today.

So, let's dive deeper into the modeling and analytic tools provided by Pacific Northwest National Laboratory. We are pleased to welcome Xiaoyuan Fan from Pacific Northwest National Lab to discuss dynamic contingency and analysis tools for extreme wildfire event planning. Xiaoyuan?

XIAOYUAN FAN: Thank you. Hi, everyone. This is a Xiaoyuan Fan. I'm a senior policy and research engineer at Department of Energy's Pacific Northwest National Laboratory. With this opportunity, I'd like to present our research on dynamic contingency analysis tool for extreme wildfire event planning. Next slide, please. Thank you.

PNNL team has developed contingency analysis tool, also known as DCAT, to help utility engineers to understand what the impact of extreme events on power grid and help them identify the weak spot in grid. We evaluate and identify mitigation procedures to prevent cascading outage process, which sometimes can lead to a city blackout. DCAT is a single tool that automatically simulate and analyze cascading sequence in actual grid systems. It also integrate model for protection systems integrated with the generation, transmission, and the load. Moreover, DCAT's unique computational scheme prevent overloading of the software algorithms, while still including orders of magnitude more scenarios and data from extreme events. The results show system operators how the electric grid would look like at any moment, so they can determine when the grid would be vulnerable to a cascading event, then make better plan for the future.

DCAT's capability has been adopted by industry collaborators to improve grid reliability and resiliency. DCAT is also 2018 R&D 100 award winner. Next slide, please.

The increasing frequency and the severity of wildfire is threatening the electric power grid and the public safety in the West. This figure illustrates the wildfire points in 2019 within the U.S. western interconnection. It is also important to understand that, in addition to the direct wildfire danger, precautionary shutoff of electrical service, as well as other utility mitigation plans, should be also reviewed and evaluated comprehensively. The PNNL team can provide a DCAT-based framework to evaluate and visualize the impact of wildfires on electricity infrastructure and potentially other interdependent infrastructures.

This framework could be applied to historical wildfire event evaluation. The simulated wildfire impact can be compared with other available event records and observations. And the impact of the wildfire on the power grid can be evaluated through the integrated resiliency and reliability metrics. Moreover, the corrective actions generated by DCAT can be included to analyze potential wildfire mitigation actions, and the simulator results shared among different stakeholders to explore or evaluate other cost domain mitigation actions. Next slide, please. Thank you.

One of the unique characteristics of DCAT is that it enables automated hybrid steady state and dynamic simulation. The impact of natural hazards, like wildfire, can be modeled as contingencies either a steady state or dynamic sequence in which the wildfire can be initiated in single or multiple locations. In addition, by simulating thousands of wildfire contingencies, DCAT automatically matches the evaluation wildfire impact with changing occurrence in the grid to find weak spots, such as the protection misoperation, allowing overloading that might ignite wildfire or lead to cascading outages.

Once a weakness is identified, DCAT determines the impact and provide the power operators with action to stop the outage before it happens. With DCAT, utility could gain at least 50% in efficiency, for analyzing grid or currents comparing to today's more manual processes. If a connection grid model have been evaluated by DCAT in ERCOT regional model, WECC planning based cases, and the production cost models, Eastern interconnection MMWG cases, and the Puerto Rico IRP cases.

To further assist the grid operator during the technology adoption process, DCAT database module and our standalone user interface application have been developed. Now, the end user has a streamlined process to formulate a contingency: run DCAT automatically, then review and compare the simulation result in an efficient and effective way. This provides a closed-loop evaluation for utility engineers to validate and verify they are able wildfire mitigation plans. And to improvise and improve for further enhance the system regarding the wildfire risk. Next slide, please. Thank you.

Here is a screen snapshot of the DCAT database and a visualization module. The user can easily navigate through the whole process of the system contingencies, reveal system status in both tabular format and [INAUDIBLE]-based count format. Time domain simulation data, including frequency, voltage, and power flows could also be pulled from the database to identify protection system behaviors and the cascading sequence with high resolution data. In the past two years, the team has also been active in developing reliability and resilience metrics and integrating them into this module. As a result, different combinations of scenarios, events, and contingencies now can be ranked and filtered. Next slide, please. Thank you.

Over the past five years, the PNNL DCAT team has applied DCAT to analyze a multitude of interconnection-level analysis. Many of those are not particular for Western interconnection. In this slide, it shows one DCAT analysis for the 2011 U.S. Southwest blackout event. Based on the description in the FERC/NERC poster event showing the report, and also information relayed from the relay to the industry standards, we integrated more than 7,000 protective relays, and several [INAUDIBLE] into this analysis. Such as the [INAUDIBLE], the time of our current relay at multiple substations, as well as load shedding schemes in several regions.

Here are the results comparison for the WECC [INAUDIBLE] event. The left-hand side is the result in the FERC/NERC report published online, and the right-hand side is the DCAT simulation results, which is based on autonomous action of this protection models in DCAT.

Overall, phase one to phase six of the whole event were successful simulated with the full protection model in the Western grid. And the PNNL DCAT team is ready to extend such capability as support WECC utility members for extreme wildfire event planning. Next slide, please.

It should be recognized that wildfire threats are evolving over time and may be different for different utility companies. So, domain use case should be formulated to deliver value propositions for different stakeholders. DCAT can be used to evaluate those domain use cases regarding the dimension of time, grid modeling specifications, and natural hazard model. More importantly, by interfacing with other wildfire spreading models or tools, such as the following one, presented by PNNL colleague Mark, for forest management and fire risk evaluation, DCAT can simulate thousands of future wildfires scenarios. Then extract from the actionable intelligence based on the stochastic impact evaluation.

Grid operators managing wildfire conditions would benefit from such DCAT-based framework to help them understand the impact of complex wildfire contingencies and provide effective decision support during those emergency response situations. Next slide, please.

Here is the example to show DCAT's flexibility we're interfacing with another PNNL tool, EGRASS, to enable geolocations of natural hazards run risk on infrastructure. It can be hurricane, wildfire, and other extreme events. The combination of DCAT and EGRASS has been demonstrated in analyzing Hurricane Maria's impact on Puerto Rico electricity infrastructure, through DOE's coordinated support to Puerto Rico grid restoration.

EGRASS provide advanced web-based visualization platform that can be leveraged and modified to provide grid operators and [INAUDIBLE] with highly valuable simulation awareness. It can also quickly estimate the impact in population, and the event of the effect on nearby grid assets, such as transmission towers, substation, distribution lines. Such DCAT and EGRASS combination could be extended for wildfires, and it's also possible to interface with other tools to form an end-to-end solution package. Next slide, please.

In summary, PNNL team will develop and to provide a DCAT-based framework to evaluate and visualize the impact of wildfires on electricity infrastructure to mitigate service disruptions and improve resiliency. Licenses for DCAT are available for research, trials, and the commercialization. Here, I also want to thank our industry collaborators. They are ERCOT, Siemens, Bonneville Power Administration, General Electric, and EPRI. Additional users, utilities, and vendors are more than welcome. Next slide, please.

Thank you. If you have any questions or feedback, feel free to reach out to me or any PNNL staff members listed here. We look forward to hearing from you. I also include a selected list of DCAT publications in next slide for your quick reference. Thank you. That's all from my side. I'll return the state to the host. Thank you.

MEREDITH BRASELMAN: Thank you so much. We appreciate it.

Now we're going to turn it over to Mark Wigmosta, also of PNNL, to talk about sustainable forest biomass for fire mitigation. And, Mark, we can see you, and I think we can hear you.

MARK WIGMOSTA: All right. Well, thank you. It's my pleasure to be part of this webinar. I'd really like to acknowledge our U.S. Forest Service collaborators from the Pacific Northwest Research Station, led by Dr. Paul Hessburg. Next slide, please.

Well, as many of us are aware, there's ongoing efforts to both improve forest health and reduce wildfire fuels that are focused on reducing canopy cover in overstocked forests. And this is usually accomplished via either mechanical thinning and/or prescribed burning. Now, the real objective to this effort is to return the landscape to be more consistent with a natural fire dominated landscape. That is really characterized by a more frequent but less intense wildfire. Much less of the mega fires that we are currently witnessing.

Now, once accomplished, this has the potential to reduce risk to the electric transmission distribution infrastructure. And if a fire were to occur of lower intensity, there's also the potential for reduced post-fire hydrologic impacts, such as landslides, flash floods, erosion, sedimentation, that accompany a storm on a fire-damaged landscape.

Now as part of this restoration effort, there's also the potential to leverage these investments to also achieve hydrologic benefits. Potentially increase snowpack, increase annual flow volumes, and potentially increased critical summer low flows. All of which can result in increased flow to the hydrosystem and potentially power production.

Now there's also economic and benefits to society through collection of the residue, following treatments for bioenergy.

And what we've developed with our Forrest Service colleagues is a decision support tool that can be used to evaluate the tradeoffs between fire mitigation, evaluate subsequent hydrologic conditions, look at available biomass, both commercial and that would be available for bioenergy, and the associated economics. To really help stakeholders and decision makers evaluate and prioritize their locations for treatment. Next slide, please.

So let's, again, we have these four main objectives. Obviously, wildfire being one of those. And then we quantify those under different restoration scenarios, using several first-order metrics. And really what we're trying to do, then, is use these metrics to quantify, again, reduction in wildfire risk and smoke emissions. Look at available biomass, impacts of streamflow, and the associated economics.

And for fire, we use a couple metrics as an index of burn intensity, namely flame-length and crowning index. We also look at total carbon release and to particulate size classes and smoke emission. And I should say that all of this analysis is being done at about a 90-meter spatial resolution. Just because of the natural heterogeneity in the landscape, and important topographic controls on how fire can respond and how the forest grows and responds to treatment.

Now, in terms of biomass, we look at both merchantable and nonmerchantable available biomass as part of one of these restoration projects. Again, the nonmerchantable would be residue for energy after the treatment. We look at hydrology, namely snowpack characteristics if it's a snow-dominated system, and streamflow, and how that's impacted by treatments. And as I mentioned previously, we'll look at economics. And, in the case of a residue for energy, we look at cost to collect, cost to process, and cost to haul to an endpoint. Next slide, please.

Now what I'd like to do is just kind of walk through briefly an example of each one of these kind of main metrics. And we'll take a look at one metric that we're using to quantify in high spatial detail burn intensity before and after treatment. And that is flame length, which really indicates the likelihood that direct fire suppression is an option, and whether crown fires will initiate.

And if we can look at the figure, we can see that in this example, without treatment we have a fairly substantial flame length, and that's reduced significantly when we have treatment. So, those are the kind of metrics we're going to look at when we evaluate how effective different treatment scenarios might be for that objective. Next slide, please.

Now, removal of forest canopy cover, whether that be through treatment to reduce fuel loading, or as the result of a wildfire, can have a significant impact on resultant streamflow. And this is particularly true in snow-dominated basins, which really characterize a lot of the runoff production, particularly in the Western United States.

And just as a quick example, in this top panel we look at times to the snow water equivalent, which is basically the water holding capacity of the snowpack. In an open area, on the left; in a forest, in the center; and within a gap within the forest on the right. The black dots are observed snow water equivalent, and the red dash is our model simulation of snow water equivalent. And really kind of take-home message in this location is that upper-right figure, where we compare snow water equivalent in the gap, shown as the red, at the same scale as snow water equivalent in the adjacent forest, known as the blue.

And what's really interesting is that we can see that the peak water holding capacity, the snowpack at the start of the melt season is about twice as high in the gap as it is in the forest. And snow remains in the gap about three weeks longer. Which can lead to increased flow volumes, and potentially increased summer low flows during some of the critical times in the water, here. Next slide, please.

Now as I mentioned, we also look at collection of residue for bioenergy. And this is an example of some work done in the Wenatchee basin, where on the left figure, we're looking at delivered cost of residue that was chipped. And again, we account for collection of that residue off landscape, processing near the road, and then hauling to, in this case, three potential endpoints. The figure on the right shows the road network that is used to transport that material. And it can consist of dirt and gravel forest service roads, or all the way down to paved roads.

And really, what's interesting in this analysis is the importance of the road network on the final delivered cost. And that's, to a large extent, a function of distance traveled and the road surface type. And what we found was that, this example, that the vast majority of the chip residue could be obtained at various target cost using just a single mill at Leavenworth. And that's really because the Entiat, Leavenworth, and Wenatachee locations are all connect by paved roads, which have a lower transport cost rate.

So, this really illustrates that when we try to look holistically at this, we really need to look at high spatial detail, both for the biophysical processes and for logistics and economics. Next slide, please.

So really, what these metrics that I first introduced in slide three, and we walked through a couple those in the last couple slides. Again, at 90-meter spatial resolution, some of the rends around hydrology, we may roll up to the sub-basin level. But they feed this decision support tool that was developed and is used by the Forest Service. And we can then use that to examine tradeoffs, again, between wildfire, water, bioenergy, and economic sustainability.

And this is just a quick example for a principle-based restoration scenario, where you're kind of trying to balance hydrology, wildfire mitigation, available biomass, in an economically sustainable manner. And what we can see in the top panel of this, the priority locations for forest treatments are shown in warm colors. And again, these are based on these derived benefits to our objectives of hydrology, fire, reduction in smoke emissions, biomass, and economics.

Now the lower panel shows the priorities if we just looked at one of those objectives by itself. For the four feed up into that upper panel. And clearly, there are tradeoffs going on. And what's valuable about this decision support tool is, you can weight priorities. If, say, in this example, wildfire mitigation or reduction in smoke emissions is a higher priority, you could then weight it higher at the expense of the other objectives. All those weights have to sum to one. But you can start to look, in a transparent manner, what are the actual tradeoffs that are occurring when you kind of work through this decision-making process?

And I should say that once you've selected a series of priority locations for treatment, all of that information that we've developed to drive, that inform the decision support tool, is all available, you know, tons of biomass, and changes in inflow volumes, and pretty much everything we've looked at. So, it's a pretty powerful tool. Next slide, please.

And I just sort of wanted to close with, again, acknowledging this work with our collaborators, the U.S. Forest Service. And we've been working together on developing this tool and applying it for a number of years now on a number of projects. And we've got a couple, three active projects as we speak. It's starting to get a bit more mature, although we're always working to improve the tool as we move forward. And next slide, please.

Finally, if you have any questions, please drop me an email or my colleague Paul Hessburg. Thank you.

MEREDITH BRASELMAN: Thank you so much, Mark. We appreciate you being here with us today.

Now I want to invite Andre Coleman to discuss multi-sensor data fusion for active wildfire monitoring. And Andre, I can see you, and let's do a quick check, and the floor is yours.

ANDRE COLEMAN: All right. Very good. Thank you, Meredith. Yeah, it's really great to be here. Thank you for the invitation.

I guess, first off, I want to acknowledge all the project leads here. This is an effort that has a lot of dedicated folks involved for doing better in the world here. Next slide, please.

So, PNNL has really been involved in disaster management and response activities and mitigation activities, as we just heard from Mark, around probably the last 15 years or so. And there's a few overarching questions that we ask around these events. And it's really about what the spatial extent of the hazard is, the timing of the hazard, both in terms of what we're observing but probably more importantly, what we're forecasting for the hazard. We also assess populations that are at risk. And I think for this group in particular, understanding the infrastructures that are impacted or forecasted to be impacted.

And we really take a multidisciplinary approach at this, where we have heavy reliance on remote sensing from satellite and airborne and UAS, or drones. We also have the interdependent infrastructure modeling. We heard about that earlier with the DCAT tool. We integrate physics-based modeling for [INAUDIBLE] flood and wildfire, both to really understand current system states as well as for forecasted states.

We rely heavily on data driven modeling. Certainly, machine learning has been a part of our workflow for many years. And all this is really underpinned by a best practice systems architecture and software development so we can really drive these research codes out to more operational systems.

We also look at these all-hazard events through the different phases of a disaster event. Both the pre-event, the peri or within event, and post event, and we'll look at that in a number of ways. And this talk really is going to be more focused on the imagery-based damage analytics for the. Next slide.

So, probably not a big surprise to folks on this call that if we look at long term trends globally over the last 35 years, we see significant positive trends and economic loss due to disaster events. And different flavors of disaster events, you can see there, have varying increases. But I think that the message is that all these types of events are increasing.

And we also see that with that we have the frequency, the magnitude, the velocity, the intensity of these events really is also increasing and requires adaptations in the way that disaster management operations are taken.

And really, what, I guess one aspect of that is really around, we have a lot of available data out there to help with the decision-making process and understanding and getting a situational awareness. But currently I think most disaster management operations are not really equipped to take in that variety and velocity of data that is coming in. And we know, too, from the disaster management community that the requirement, as it's always been, is to get accurate, timely, and comprehensive impact assessments. And be able to do that consistently throughout the duration of an event. Next slide.

So, I'd like to introduce to the group a software suite that that's been developed at PNNL. It's called the Rapid Analytics for Disaster Response. This is a software suite that really relies on overhead imaging. So, as I noted earlier, satellite, airborne, drone, or UAS type data. And we really are taking this all-hazards approach, where we can use these specialized sensors out there to detect the hazard itself, as well as the impact left by biohazards. And we're looking at this in a lot of different domains for flood detection, disrupter detection, vegetation damage, and certainly in the wildfire-monitoring space. Next slide.

So, I wanted to take a moment and really look at the 2020 a wildfire season. And I think, as we all know, it was a pretty bad fire season. We had 10.3 million acres burned in the U.S. And just for context, if we look over the last 10-year average, that's 1.4 times higher land area that was burned. And then if we look at the period before that, from 1990 to 2000, that's three times higher than that earlier period.

And as we look at some of those big, long-term trends, we really see that the number of fires will oscillate a bit. But the long-term trend is really more a flat trend. If even a little bit negative. But really, where we see a strong positive trend is in the total acreage burned for each of these fires. And that's really been evidence, as we saw in California and Colorado this year, where these states recorded some of their largest wildfires in recorded history. And of course, all this amounts to lots of structures lost, and significant economic impacts. Next slide.

So, as we've been working in the wildfire space here, and really understanding what some of the current needs are out there. One is really around this need for high resolution satellite imagery to help with that situation awareness demand. And traditionally, we've used imaging aircraft for a lot of these fires, but these aircraft are also in high demand and tend to be prioritized for high complexity fires. More and more of the type 1 and type 2 fires.

We've also heard the need for more persistent monitoring over really any given fire. And so, as much as 10-to-15-minute intervals, but depending on who you talk to, maybe that becomes more several hour intervals.

We also understand that the need for automated algorithms to take the imagery process that generates analytics, and really start to move away from the human analysts' image interpretation. And maybe shift that role to doing more and more QA work on those automated analytic results.

There's also a need to image at higher resolutions. So, we have satellite sensors out there that are commonly used, that image at 375 and one kilometer pixels, which is fairly coarse, especially if you're trying to find spot fires and deal with those.

There's a need for automated early fire detection, as well, in a number of domains. And also, this need for semi-continuous fire behavior forecasting, where we can use current system states and current available information to drive those fire behavior models. Next slide.

So, the effort that we're working on around this is this idea that we're addressing some of those technology needs that I just talked about, using a whole variety of satellites that are really well positioned for tackling the wildfire problem. And not every observation satellite is equipped for that. And so, the idea is we can take these satellites. They all have different orbit trajectories and timings. But the idea that, by using all these different stats, that we can get daily, if not that multiple snapshots every day.

And I think one of the important parts of this: These are not state-specific. They're not region-specific. But, really, the capabilities being developed here at PNNL around this are really globally effective. Next slide.

So, our wildfire components of RADR. The real goal here is developing out an automated, end-to-end, cloud-based system that provides open data. So, anybody who wants to get the data can have the data. The system is working to retrieve that satellite imagery automatically. We're relying on satellite imagery, but that's really also open data. So, we're not relying on commercial assets at this point. And, through this whole system, we're providing that situational awareness. So, through those automated algorithms, we're generating the active fire front, detecting spot fires, classifying the scattered heat where the fire's moved through already, getting at the post-burn intensity, and also understand where those unburned areas are.

All this is packaged into a timed series of results. So, you can look at the dynamics of the event, and they're distributed through the website mobile app and web services. Next slide.

Just real quick, I know my time my time is really short, but some of the post-burn analytics here. Looking at burn intensities and coupling those with critical infrastructure to really help with understanding where you have maybe specific needs for asset replacements, where some of the fire areas were burning more intensely. We can also use these data for post-fire flood and debris flow risk modeling. Next slide.

So, the final slide here is really taking these satellite observations and integrating that into wildfire behavior modeling. And the idea is to take that current state of observation from the satellite, as well as deriving a lot of the data needs for fire behavior modeling, and then using the fire behavior modeling to help fill the time steps required for a given fire. Really until we can get that next satellite observation, and then repeat that process. So, next slide.

So, yeah, this is the entire team. Also just wanted to acknowledge the Department of Defense Joint Artificial Intelligence Center, and DOE's Artificial Intelligence Technology Office, who also sponsors the initiative. So, thank you for your time.

MEREDITH BRASELMAN: Thank you so much, Andre. We appreciate it.

So, now I want to introduce our next speaker from Lawrence Berkeley, Qing Zhu, who is going to discuss XAI models of wildfire risk and risk management. And there we go.

QING ZHU: Thanks. Thanks so much. So, my name is Qing Zhu. I'm from Lawrence Berkeley National Lab. I'm a research scientist working under our disturbance and ecosystem modeling and machine learning. So, today I wanted to share some of the ongoing work and also the future plan of these XAI activities. So, this is XAI models of wildfire risk and also the risk management. XAI here means Explainable Artificial Intelligence. It is a integrated framework of process-based model and plus the artificial intelligence model. Next slide, please.

So, there are two overarching goals. One is to map the wildfire risk, but with variable temporal scales. And for the input from daily to weekly and all the way up to seasonal scale. For example, six to eight months before the fire season. And they have different meaning in terms of the mitigation, because, over short term, probably we can do some power line shutdown or some firefighter resource reallocation. And over a long time, we can actually do a lot of other things. For example, forest thinning. It's the mitigation and the risk. It's highly sensitive to temporal scale. And that's one of the strengths of this XAI framework.

And the second overarching goal is to evaluate the impacts of potential management practice on reducing the fire risk. For example, we can do all those major operating mitigation practice in this integrated model, particularly in the process-based model that I will explain later. Next slide, please.

So, there are four specific objectives. One is, we will develop and test this hybrid modeling framework with mechanistic modeling, and also with the AI model components for risk assessment. So, the mechanistic component of this XAI is to enhance the model interoperability. And the AI component, it can run really fast and then auto adjust when the data are updated. And so, we combine them together to have those, both accuracy and also the modeled efficiency.

And the second objective is to model the wildfire risk probability dynamically across space and time. For example, during the wet season, we can have an initial guess of upcoming [INAUDIBLE] fire risk, and then continuously update the fire risk in a near real time manner from days to months.

And then the third objective is to model multiple management practice, and also evaluate their potential impacts. And it's really time sensitive, as I mentioned before, because it's over regions that have high fire risk. And it's already in the fire season or right before the fire season. Then maybe we can test, well, what if we shut down some power line. Or over some high-risk regions in the process-based model, and then simulate the potential impacts and see how much the fire risk can change because of this mitigation. And if it's long term, then we can do more things about reducing the surface fuel availability.

And then the fourth objective is to continuously improve the risk model. That's actually one of the strengths of this framework. It can auto adjust given more and more data coming in as the time proceed. Next slide, please.

Here is a technical summary. On the right top, that's what usually people use, published in the literature, and people use to estimate the fire risk. People usually use process-based risk index that combines surface climate and also combined fuel condition to come up with an interpretable risk map. However, it is less accurate.

And the second major approach in the literature is purely AI-based, or machine learning based. That's the right bottom figure. And it's highly accurate. People do acknowledge that. But it's less interpretable, and it's the lack of physical constraints and many times it's overpriced. Given that wildfire is a extreme condition and we don't have many training data sets on the wildfire modeling.

And our approach, on the left. We have several steps. So, step one, we have a process-based fire model component that simulate the processes of ignition, suppression, fuel condition, and also the climate factor. They're all dynamically simulated within this land surface model. And we combine those fact drivers, and also the model simulated fire activity, and then we use a AI surrogate model to surrogate the fire behavior in the process based fire model.

In that way, we come up with a simulation tool that can run very fast. And also, then can be easily centralized. And the initial step, and we use real observation to constrain this AI surrogate model, so that the model can be both fast and accurate. And also, it has some physical constraint, because it can't pretrain or came from the process-based model. And finally, we can use this model to simulate via various scan also fire activity. Next slide, please.

So for the management, what people usually do in the literature is we need to run actually the process-based wildfire model. Because management actually modify, for example, it modifies, if it modifies service field availability, then not just the fuel availability is changed, but also the end service property change. Everything, a lot of thing has been changed. So, using machine learning model, it's not feasible. So, we had to rely on the physical model. But the physical model is also highly sensitive to its initial condition in the model parameterization, and it's less efficient.

So, we wanted to integrate that into our surrogate model approach. That is on the left. We have step four, additional component. That is, we incorporate different kinds of management activity into this process-based fire model. And we use our surrogate model to evaluate the potential impacts from the management activity. And particularly with variable time scales.

We still apply all kinds of management activity, but the actual impacts, they are independently assessed. And now, we can come up with the best management practice that is suggested by the system. Next slide, please.

So, here is some preliminary results. I want to highlight that the baseline is the published work in 2020. I use a random forest model, that's a traditional machine learning model. And our XAI model, also using the same data sets, and do the same risk assessment mapping. On the left, that's a spatial illustration, and on the right, that's a temporal demonstration. X-axis is the month in advance. That means we have one month ahead of the fire season, all the way up to eight months ahead of fire season.

So basically, spatially, our risk estimate overlap with the actual observation much better, compared with a baseline model that is published work. And also, on the right, our model have high accuracy with the short leading time. That one month leading time.

I also want to highlight that, across a longer lead in time, to eight months leading time, our model position doesn't decline that much. It still is very high accurate compared with the baseline model. So, that means we can do not just the short-term mitigation but also long term mitigation based on this XAI framework, which is very reliable across timescale. Next slide, please.

So finally, in terms of deliverables, in three months, we are going to have a wildfire early warning system that give us the estimate fire risk with variable time scale, from daily leading time, all the way up to seasonal leading time. And in six months, we are going to have a wildfire mitigation tool that is actually based on this early warning system. Or early warning tool. The mitigation system will ask, what if we do this kind of mitigation practice, and ultimately, automatically update the risk map to demonstrate the potential impacts of the mitigation activity?

We can apply whatever management in this mitigation simulation. But the impacts really depends on the mechanism or depends on the timescale, whether it is a daily to weekly leading time, or it's a monthly to seasonal leading time risk management.

That's all from my side. Thank you so much.

MEREDITH BRASELMAN: Thank you so much. Appreciate it. As a reminder, please continue to submit your questions in the chat box. And please make sure you reference the speaker or the topic so we can direct it to the right person at the end.

So, now I want to introduce Robinson Negron-Juarez, also of Lawrence Berkeley, who will outline the predictability of fire behavior and effects in the wildland urban interface in California. And, Robinson, it looks like you've got the ball, and you're good to go.

ROBINSON NEGRON-JUAREZ: Thank you. Can you see my screen?

MEREDITH BRASELMAN: We sure can, and we can hear you too.

ROBINSON NEGRON-JUAREZ: OK, perfect. Thank you so much. Thank you to the Office of Electricity for inviting me to present in this panel.

My name is Robinson Negron-Juarez. I'm a research scientist at Lawrence Berkeley Lab in the environmental science area, where currently I lead the wildfire research.

Today I want to talk about the predictability of fire behavior and effects in the wildland urban interface in California.

I would like to start my presentation with this animation based on GOES images. On the top, you can see the date, starting with the year, the month, and the date, and the time is 6:57 a.m. And this animation is for the campfire. We know that it had a high number of fatalities: 85. On the screen, you can see the time where the GOES captured the first incident of the fire. On the left, you can see the Paradise town. It's about six kilometers away in a straight line from the started fire to Paradise. On the bottom of the screen, you can see that clear part, to give you some reference.

So, I mentioned the fire start at 6:57. And then in this animation, I'm going to stop here the animation at 7:47 a.m. So, in about one hour, the fire is spread about six kilometers from east to west and reach the border of the Paradise town. After that, the fire moved from north to south. The colors here represent the intensity of the fire, with red color less intense fire, and the white or yellow color the most intense fire.

So, we have these satellite images from GOES every five minutes, which is a very high temporal resolution. Even that's partial resolution, and of course it's about two kilometers.

So, having this high frequency of images, one question that we can ask is, how can we use this data to predict fire behavior?

And this is our approach or strategy. Currently, we don't have funds to develop this system, but I would like to mention what we can do here.

So, we have a huge number of biophysical variables in order to predict fires. We'll have vegetation type, vegetation structure, vegetation conditions, soil type, soil moisture, and when I mention soil moisture, I mean all the hydrological characteristics of the area. We've had several topographical features, including slope, aspect, and elevation. And wildfire territory, including spread, burn rate, and severity. All this data is available through satellites. And on top of that, we have our weather or climate data. Currently, the weather prediction in California are really good, about dangers ahead of time.

So, we can include, put together all these data in a machine-learning framework. It's pretty similar that Qing Zhu, our previous speaker, presented with great detail.

So, something that we need to do here is, for instance, Qing Zhu, he focused on the fire starting. So, we need to, and after the fire start, we need to try to predict how the fire is going to spread. And how we do that is using the satellite images from GOES.

And then, the model, we're calibrating cells interactively with this five-minute images in order to predict ahead of time how the fire is going to, what is going to be the behavior. Where the fire is going to spread. And this is very important, because currently there are several efforts to launch satellites to monitor fires. And in a few years, we will have a lot of data monitoring fires with high spatial resolution and high temporal resolution.

So, we need to use this data training and machine learning model to predict the fire ahead of time. And when we have that, we can ask questions. For instance, what is the mechanism driving the particular fires? And that later can be included in physical models in order to improve those models.

After the fires, in the woodland area, that vegetation is going to regrow. And that is important because that's going to be the fuel for the next fires.

So, we need to ask how the vegetation regrows after fires.

And this is the case. To answer this question, I want to show you this case, for the Steamboat fire, that happened in 1990. On the left, you can see that Yosemite National Park, with all the vegetation types and colors. The little flame, the red flame, I'll show it with my mouse. My cursor. Shows the location of the Steamboat fire.

The center figure on the top shows a timed series of images, before and way after the fire. And on the bottom of the figure, you can see the surface reflectance. And this is the data that we get from the satellites. And you see different bands are going to give you different response with respect how the vegetation is going to grow. So, we need to use that information. We can use this information in order to predict how the biomass is going to regrow. And we know, from studies, the surface reflectance, specifically near the infrared, is really close with biomass, with biomass regrowth. That is not related with recovery of species. With that, recovery of species takes centuries to an area that was born or disturbed to recover to the same species as it was before. In this day and this case study, I can only tell you about the biomass.

So, when we put together a satellite data and field data, so we can validate and improve models.

And we have done that for the Amazon. In the Amazon, the three main forms of the disturbance are windthrows. That happens when a strong wind knock down trees. And that is shown in the fever on the left. And just to give you a reference, this little blue dot, that is me. We have also clear-cut. That is related to deforestation. And burning.

So, we found that in this case, for the Amazon, the surface reflectance from Landsat not only follows the trajectory of the biomass regrowth, but also match exactly when the biomass recovery to pre-disturbance condition. Or, three, respect to windthrows, clear-cut, and burning.

And we put all this data into the model we are using: FATES. FATES stand for the Functionally Assembled Terrestrial Ecosystem Simulator. That is the main product of the next generation ecosystem experiments or energy topics that is a project funded by DOE.

So, FATES was able to reproduce not only that trajectory but also the time of biomass regrowth for clear-cuts and windthrows. When we did this study—we published this study last year—the fire model was not ready. Now it's ready, and we are going to do a subsequent study focusing on fires.

Summary: We can implement a machine learning model for ahead-of-time, accurate prediction of how the fire is going to behave. And that is important, for instance, for every worries. We have created a framework that integrates remote sensing field data modeling that predict biomass regrowth after fires. And we integrate these capabilities. We can produce a reliable short- and long-term prediction of fire behavior and effects.

And just to finalize my presentation, fires happen for different reasons. And now the most sophisticated model will be able to tell you where the fight is going to start. This is the case for the El Dorado fire, that was here in Southern California [INAUDIBLE] Southern California, that was produced by a gender reveal party. No way we'll be able to predict that. And that fire burned for about one month. But when we can now predict when the fire can start, where the fire start, we can predict where the fire is going to move. Where, ahead of time, where the fire is going to spread. And this is a picture I took for the El Dorado fire from the window of my house.

So, thank you.

MEREDITH BRASELMAN: Thank you so, much Robinson. We appreciate that.

Now we're going to turn it over to David Romps. He's going to walk us through climate modeling for California planning. And give us just a minute. We'll get your slides there. I think you may need to—oh.

DAVID ROMPS: Yes. I need to maybe share them, as opposed to running them. There we go.

MEREDITH BRASELMAN: We can see it.

DAVID ROMPS: We're in business now. Right, so, thank you for the invitation to speak. Pleasure to be here.

I want to start with this day in recent memory, just last year. August 16. It's a day that I remember very well, personally. And it's a day in which we set a new highest verifiable temperature record on planet Earth. This was in Death Valley, but it wasn't just the highest temperature ever recorded in Death Valley. It's the highest verifiable temperature recorded anywhere on Earth. So, it was really a remarkable day from that perspective.

But also in California, we had something else going on that day. In the wee hours of that morning, I was awakened, as was, I think, everyone in the Bay Area, by this siege of lightning that barreled down on the state, especially the northern part of the state, pictured here coming in across the Golden Gate. This lightning season, as people know, I'm sure, triggered wildfire around the state, leading to quite a disaster.

Less than a month—this is a plot showing acres burned every year, updated for 2020—less than a month after that lightning siege came through the state, and less than a month afterwards, we had obliterated previous records going back to 1950 for acres burned in the state of California. And by the end of the fire season, the acreage burned exceeded 4 million acres. So, actually off the chart here.

I'm going to give you a little bit of background, really quickly here, on how this lightning is made. The lightning here was the trigger for these fires. So, lightning is made by storms. And we can think of storms as a big battery, or a big capacitor. And like a battery, it has a positively charged side, and it has a negatively charged side. And it's the motion of the cloud updrafts and the water particles in that cloud colliding with each other that leads to this charging. So, the big particles, they're heavy and tend to fall downwards, whereas the small particles are light and tend to get carried upwards by the updrafts. So, they have this differential speed, so they bump into each other. When bump into each other, they preferentially give positive charge to the little particles going upwards, and negative charge to the larger particles falling down. And that's what leads to this charge separation in the cloud. And this charge separation can get so big that you end up with a lightning strike. The lightning strike is just like a spark, discharging some of that electric field.

So, if you have this lightning strike landing where the rain is, it probably doesn't do anything with regards to fire. You've got a wet ground that has been, really, rained on quite a bit. And the lightning has not much potential for starting a fire.

But if the rain is evaporating before it reaches the ground, then that is an opportunity to spark a wildfire. Or, also, if the lightning simply lands outside of the rain shaft of the storm. And that is another way that you can light dry fuels on the ground.

If we look across the United States—sorry for the busy looking plot here. But if we look across the United States, we see that lightning plays an important role. On the left here, the area of red and yellow, this corresponds to the rate of number of wildfires started in a year over the United States in each location. With yellow being lightning fires, and red being all other causes of wildfire. And there we see that lightning triggers a relatively small fraction of the number of wildfires, maybe around 15%. But we look in the right panel. This is the area burned by wildfires. Yellow for lightning, red for all other causes. And then we see, if we crunched the numbers, that about a half—or over half, actually—of the area burned by wildfire was started by lightning. And this makes sense because lightning is landing in places that are often far from humans and harder to suppress. And in the West, the area burned is dominated by lightning.

So, if we look at the balance of evidence relating global warming to lightning strikes in the United States, the balance of evidence tells us that global warming increases lightning strikes in the United States. And the way we come to that conclusion is by looking at variables—atmospheric variables—that correlate with lightning today.

And here is an example where we proposed a particular variable. CAPE times precipitation shown here in blue. CAPE is a measure of potential storm energy, and precipitation is the rain rate. So, we've got a time series of this over the entire United States in blue. And also shown is the time series of the United States of actual observed lightning strikes in red.

And we see as we go through the year that there's a very good correlation between these things. So, we can find variables like CAPE times precipitation that match very well the actual lightning strike frequency. So, we can use these kinds of meteorological variables to make predictions for the amount of lightning that will occur in, say, weather forecasts. And also make predictions for the distribution of lightning in a new climate regime.

So, we find these variables that correlate with lightning today, and then we use those variables that we have some confidence in, with regards to predicting lightning. And we apply them to output from global climate models. And what we do is we find that those project about a 50% increase in lightning over the United States by the end of the century, in a business-as-usual scenario.

And this is replicated using a variety of different proxies or variables to represent lightning. CAPE times precipitation shown on the left, here, is the one that we had proposed originally. And then, here are three others that we've checked. And, indeed, we find that the story is very consistent over the United States. That we expect this fairly large increase in lightning caused by global warming.

So, with that information, we can speculate that more lightning will lead to more wildfire. But I would argue that a 50% increase in lightning by 2100 is not actually the big story with regards to how global warming affects lightning and affects—not with regards to the impact on wildfire.

I would say the big story is the effect that the warming has directly on the flammability of the fuels down at the surface. And research tends to bear this out as being a really large component of what is causing, and will continue to be causing, increases in areas burned.

So, this is a result from John Abatzoglou and Park Williams in a 2016 paper, where they looked at the relationship between how dry the vegetation was, as caused by increases in, basically, aridity. The lower humidity in the air, the drying capacity, which is caused directed by warming. And they looked at how many acres were burned in observations, and using this relationship between how warm and dry the air was and, correspondingly, how dry the fuels were, they reconstructed what the acres burned would have been, without the amount of warming that we've already seen to date. And so here, they're showing this cartoon of cumulative acres burned, with warming, as we've had in reality, up to 2014 or so here in this plot, and without warming.

And what you see is that the warming we've already caused is likely to have already directly caused maybe a 100% increase in the acres burned because of the direct effect of higher temperatures on the dryness and the flammability of the fuels.

Now, this story will be modulated by many different things, including things my colleagues have spoken about, including changes to ecosystems, changes to the pattern of precipitation, changes to wind, for propagating the fire, of course, with regards to electrical transmission and distribution systems, potential non-lightning triggers.

And so, we need to bear those in mind to provide context for what we think is this maybe 50% increase in lightning, and maybe a correspondingly sized increase in lightning triggered wildfire by the end of the century.

So, I'll conclude there. Thank you.

MEREDITH BRASELMAN: Thank you very much. We appreciate that. Our next speaker is William Riley, also from Lawrence Berkeley. He's going to discuss attention-based, long-short-term-memory model. And, William?

WILLIAM RILEY: Well, thank you.

MEREDITH BRASELMAN: There you go.

WILLIAM RILEY: I hope that showing for everybody?

MEREDITH BRASELMAN: It is. You're good to go.

WILLIAM RILEY: Great. OK. So, I'm Bill Riley. I'm a senior scientist at Berkeley Lab. And I am going to describe some work that our group is doing with Qing Zhu, who just recently presented, on attention-based, long-short-term-memory machine-learning model. That's quite a mouthful. So, I'll go through some of the details here and what we are developing.

The overall goal is to come up with a way to estimate burned area, or to predict burn areas, of course with high accuracy. But also with flexible lead time, meaning understanding how precursor conditions lead to wildfire likelihood.

The other important thing we're interested in is having this approach be interpretable. So, it's trying to open up the black box of machine-learning approaches so that we can understand the underlying mechanisms that are implied by that approach.

And I'm going to describe to you some work we're doing in E3SM, which is the Department of Energy's global model, in which Qing and I both work. And then describe how that work is moving towards fire resolution type of approaches.

So, this example is going to be shown here looking at the GFED regions, and in particular focusing on southern hemisphere South America, northern hemisphere Africa, and southern hemisphere Africa. Because that's sort of the most recent work we have on using this approach.

But I will make this point that the infrastructure that's developed is really only limited by the resolution of the information we have, both in space and time. And that information is becoming more and more available, which is why we're moving towards California-specific analysis, for example.

So, here's what I'm going to describe to you for this study. We looked at several—six—different machine-learning approaches for wildfire prediction. As I mentioned, one of the objectives of this is to give us a way to interpret what the machine-learning model is telling us. And we're using what's called an attention mechanism, which I'll come back to in a second. But to do that. And that will help us learn more about the underlying mechanisms.

Now, one of the motivations for that is that we can help with the mechanistic fire models that are integrated in these large-scale models. But also, just for informing measurements that are needed, et cetera. This is a really important part of our approach.

We also want to make sure that we consider the transient nature of the forcings, or of the causes that lead to wildfire. So, we want to think about the months ahead of the fire season, and how that, and what happened during those months affects the current burn area.

And I just have a figure here to indicate the complexity of this. This is just showing, for these three regions, in each figure, the burned area in brown, as a proportion of the annual burned area, and the precipitation. And you can see that, although there are some patterns that sort of pop out in how these interactions go, they're quite different between the regions. And they're quite different between the other forcings that lead to wildfire.

The other thing that we really wanted to include here for the longer lead time predictions are some of the more remote ocean indices that people have used in the past, including El Nino. Those type of indices have been used for longer lead time predictions. And that's just shown here in this figure. That there are these effects that can be inferred from these ocean indices on the wildfire season.

So, as I mentioned, we looked at several different machine-learning models listed here on the right. The one that I'm going to focus and show you most of the results from is what we're calling an interpretable, long-short-term-memory. And what I mean by that, of course, interpretable is the point I made earlier, that we want to understand why the machine learning, of course, is giving us the answers it is. The combination of long- and short-term memory is illustrated here in this complex schematic. I'll walk you through it quickly. If you look down at the bottom, these different time steps are indicating that we're looking at relationships with the lead time.

So, you can imagine these are each a separate month in the past. And in each of those time steps, we have information, that are indicated by these colors, about ignition, suppression, fuel amount, for example, and climate, temperature, moisture, et cetera.

So, we can apply our attention, so to speak, to this time series. And then we can weight that. This is all using the GFED observations of burned area to train the model and better understand which variables in which time period are affecting our ultimate goal of the burned area at the top. So, that's a qualitative explanation of the approach.

Let me show you a few of the results. So, this is those three reasons I mentioned, in the rows. And then the two columns are the GFED observations on the left. And then the predictions from this, we call it the ILSTM. So, interpretable long-short-term memory model. And you can see very good correlation, at least qualitatively, between observations and the model.

Quantitatively, we made these figures here showing you the absolute error. A burned area in each of the regions, in millions of hectares, as a function of the lead time for the prediction. And the red line is the ILSTM model. And I guess the point here to notice is that it has the best or the lowest absolute error. But also, the error doesn't degrade as much as you use less and less information from the nearest time point to the burn month.

And the other important thing we can extract from this approach is illustrated here. So, I'll show you some results in a second from the southern hemisphere Africa, so let me just focus on that. The y-axis is how important a particular variable is to the prediction of the burned area. And you can see for the Southern Hemisphere Africa, the rain and vapor pressure deficit, which is an indication of the drying potential of the atmosphere, are the two dominant, important variables. Then we can look at, for a particular month during the fire season, how important a particular variable was back in time. So, for example, if we're interested in the September fire season month, down here, and this is a case for the precipitation or rain. You can see that the most important months for rain's effect on September's burn area occur in January and February. And we interpret that as the precipitation's effect on vegetation growth, and therefore fuel for the fire.

We can do the same thing for all the variables, to interpret the temporal and, actually, spatial controls on the fire during the fire season.

The other point I wanted to make about this is that there is value in these ocean indices on the prediction of wildfire burned area. And that's illustrated here. If you just look at the top figure, this is just an example. The northern hemisphere Africa large fires. What you can see is that for—and again, the x-axis is leading time months. That there is value. In other words, the error decreases when the ocean indexes included the longer lead time. So, there is value to the prediction in these longer lead times from using the ocean indices.

So, I'll just summarize real quickly here. We're developing this capability in, what I showed you, so far, in E3SM to produce highly accurate, in both space and time, predictions of burned area. And we're also using it to interpret the relative strength of different controllers in different times. And you saw some of these results that the local conditions that have stronger controls at short lead times, whereas there is a lot of information in the longer lead times from the oceanic precursors, meaning those ocean indices.

The other important, I think, and interesting part about this is that we can now say something about the underlying mechanisms controlling burned area with this approach. Opening up that black box that is so annoying to many of us when these machine-learning approaches are described.

And the other important thing, of course, I didn't mention much about it. But we can look at the spatial heterogeneity of those controllers, even within regions. They're grid cell-based. Whatever the information resolution that is available, we can make these interpretations at that spatial scale.

And as I mentioned, ongoing work is applying this at much higher resolution in U.S. and in California, specifically.

Thank you.

MEREDITH BRASELMAN: Bill, thank you so much. We appreciate that. And if everyone will give me just a moment to get our slide deck caught up here.

All right. Well, we have reached our final presentation from Lawrence Berkeley. We have Bin Wang, who is going to discuss data driven wildfire risk model and grid de-energization strategies. Bin?

BIN WANG: Hello, everyone and thank you very much, Meredith. It's my great pleasure to talk about our work and the data driven wildfire risk model and the grid de-energization strategies. And I'm a research scientist from Lawrence Berkeley Lab, and this work has been funded by University of California Office of President, as well as LBL. And next slide, please.

As we all know, the wildfires have caused serious damages to our transmission and distribution systems, as well as the electricity consumers. Let's take the state of California as an example. The state has just experienced the largest wildfire season, in the year of 2020. That more than 9,000 fires had burned more than four million acres of land. The utility, PG&E in this case, has filed bankruptcy due to the huge impact of campfire in 2018, which is caused by powerline ignitions.

However, the wildfire is not a California-only problem. It is, instead, a nationwide threat to many states in the country, including 10 out of the 11 states in the Western part, and the state of Florida, Oklahoma, Hawaii, and Texas.

It is in great need for the utility companies to come up with better and advanced wildfire risk model. And it is important for the grid operators and planners to incorporate the complex risk models with temporal and spatial complexities into their daily operations. In this case, in order to solve this problem, we have looked at previous research, which unfortunately still cannot answer many important questions. These questions include how and when and well the fires will impact the electricity system operations. And how should the utility companies incorporate these wildfire risks into a streamlined and super-fast decision making?

Motivated by this, our work is targeting at solve some of these issues by putting ourselves into the shoes of utility companies. Next slide, please.

So, the first part of our work is data-driven wildfire risk model. And the goal of this work is to not only predict the wildfire risks that are induced by power ignitions themselves, but also to predict the future fire risks, or explosion risks of transmission and distribution systems that are caused by environmental ignitions. In this case, we are leveraging a couple machine-learning models to build complex correlations between the fire risk with some external factors that include the weather and vegetation information, as well as the grid infrastructure information. Once this is done, the model will be able to tell the utility companies how and when and well the fires will ignite in their territory. Next slide, please.

From the preliminary result, the logistic regression model has achieved more than 75% of accuracy in predicting the wire-down events, which is one of the primary causes for power line ignitions. We are relying on the training data that we have collected in the PG&E territory from year 2015 to year 2019, together with the weather and infrastructure data when the wire-down events happened in history. Next slide, please.

In addition, we have also applied our model from University of California Merced to predict the wildfire exposure risk of transmission lines, based on the historical fire records. As you can tell from the left-hand side picture, the fire perimeter of the campfire in 2018 crossed over with some important transmission path. And on the right-hand side, it shows that our model has also incorporated the future climate change factors into the fire risk determination. As you can see, the northern part of California will have more wildfires of 30 years from now ahead. And the high fire-risk region will also cross over with some important transmission path, which needs attention by the utility companies. Next slide, please.

The second part of our work is on data-driven decision-making framework. And the goal of this part of work is to develop a streamlined but super-fast decision-making process. Traditionally, a [INAUDIBLE] analysis and cascading failure analysis used by many great planners and operators to analyze the grid extreme events case by case. However, this process requires significant computational resources, and it's becoming very challenging for utilities without that much computational resources.

And our approach here is to run massive number of wildfire scenarios on the supercomputer at Berkeley Lab in parallel and use an ensemble of simulation results as training data to our machine-learning and AI models. The learn model will mimic the function of the contingency analysis and cascading failure analysis but achieve much better computational efficiency so that the utility companies can use it to derive the de-energization operations in a much faster way. Next slide, please.

So, this is a case study to indicate the decision-making process. As you can tell, on the left-hand side, the grid topology we used based on GMLC RTS test case with optimal load shedding. On the right-hand side is a case without optimal shedding. Suppose fire impacted the two lines of the grid topologies noted by the dashed lines in the original topology. And we can subsequently determine the overloaded lines, labeled by rat lines here. Next slide, please.

For the cascading failure analysis, if we have a transmission line impacted by wildfire, labeled by red here on the right-hand side, and subsequently line set number three and line set number four in green, and line set number five in yellow, will subsequently experience light outages.

So, those examples will demonstrate how the traditional approach will determine the low shedding areas and generator operations, as well as the optimal vulnerability analysis for the grid. Next slide, please.

However, without using the traditional approach. And we have successfully converted the decision-making process into a multilevel classification problem. Well, a massive number of simulation results have been generated as ensemble training data. The features as input include the generator status, low profile, as well as temporal and a special complex wildfire models.

And the output will include the generator control schedules. For example, if it is going to ramp up or ramp down, as well as load shedding and the cascading failure, identification of each bus and line in the grid topology. Next slide, please.

In this case, we are using RTS-GMLC as a baseline test case. And we are extending our algorithm and model to a much larger scale case for the Western United States. Next slide, please.

The preliminary results indicate that more than 65% of accuracy in predicting the line overloading and cascading failure lines using support vector machine, which is one of the very promising machine-learning techniques we used in our study. Next slide, please.

For the cascading failure case study, the SVM can also achieve more than 95% of accuracy in determining the cascading failure lines, as shown here in this slide. So, with this capability, the utility companies should be able to not only predict the high-risk regions in their territory, but also they can use this model to predict the vulnerability of their great assets by determining how likely a line in their grid topology will go overloaded. Which of the generators in their territory will need to be ramped up or ramped down during these emergencies. Next slide, please.

As we have, we are just one year into this project. This is our preliminary results. And we are continuing doing work to improve the prediction performance. So, a couple limitations, as we identified, include the small test cases. In the future, that we will extend our model to the Western scale. So, that will need more computational power with better accuracy model. And secondly, the data set we used is limited. However, we have just scheduled regular meetings with PG&E to talk about the operations and the meteorology research in order to mitigate the wildfire risks. Hopefully in the future, we will have more data set on the grid infrastructure, as well as the wildfire behaviors.

In terms of next steps, we are investigating multiple machine learning techniques and compare their performances in the wildfire risk prediction, and also investigating the approaches to maximize reliability by minimizing network upgrade cost, and by placing more distributed energy resources in the distribution grids that will potentially enhance the greater resilience.

And finally, the network connectivity and topology has not fully been incorporated in our study yet. So, we will leverage another kind of machine learning techniques, which is deep graph-based machine learning, that will automatically encode the temporal and a special network complexities. So, hopefully this will help with prediction accuracies. Next slide, please.

This is our team. And special acknowledgment to Professor Charles Jones, who is the principal investigator of the UCOP Project that we are working on. Thank you, everyone, again for your time. Looking forward to working with everyone in the future.

MEREDITH BRASELMAN: Thanks very much, Bin. We appreciate it.

And now we have our final presentation of the day. This is David Judi from PNNL, who is going to discuss RIFT, the Rapid Infrastructure Flood Tool. And David, the floor is yours.

DAVID JUDI: Thank you. I gave a related talk a couple weeks ago that some of you may have heard of, which was about accessing an archive of simulations. Today, I'm going to talk about how we actually do the simulations of the relationship to fires. So, next slide.

So, first some context that I shared previously, also. One of our objectives here is to really develop and apply state-of-the-art infrastructure analytic capabilities that can support a broad range of infrastructure protection-type questions. This includes looking at infrastructure fragility and resilience, looking at dependencies on natural systems, or even the coexistence within natural systems. Interdependencies between infrastructure systems, and the evaluation of the services that those infrastructure systems may ultimately provide.

As you all may be aware, weather extremes are some of the most frequent and significant causes of widespread infrastructure destruction. With that in mind, we've developed a number of capabilities that help us characterize these hazards, such that the information can be used to understand cascading effects across these systems. These are intended to be applicable for planning, response, and recovery activities in these extreme events. Next slide.

One of the areas we've spent a great deal of time thinking about is enhancing situational awareness during extreme events, specifically in the context of flood events. The questions that are listed here, my colleague Andre Coleman touched on. Really, questions that have driven some of the capability development to help understand and characterize what these events look like. And ultimately, get an understanding, how many people might be at risk, and what infrastructure systems are at risk.

So in the context of floods, how do we support flood events? Well, we have three primary approaches which we may take. One being real-time modeling and simulation, or using the predictive capabilities to develop characterizations, which is today's topic. They also use imagery-based damage analytics, which we heard from Andre Coleman, talking on wildfire, but a similar process for floods. And then accessing previously simulated events that may be stored in an archive, which is what I talked about a couple of weeks ago. Next slide. Next slide. Thank you.

So, what is RIFT? As has been said, it's the Rapid Infrastructure Flood Tool. It's a two-dimensional, hydrodynamic model. It has been designed with emergency response in mind, and a particular focus on rapid. This pertains, really, to the way we've formulated the numerical implementation and the computational technologies that we used to actually run the software.

And so, we've made some deliberate decisions on things like the type of data that we ingest into the model. We've emphasized use of data sets that are readily available, and available at CONUS scale. So, we can perform simulations really at any location at any given time.

The primary application has been towards emergency response, but we think the simulation capability really has applicability across the entire response timeline, including planning, response, recovery, and mitigation activities. Our primary interest has been in doing this in coordination with infrastructure owner operators, and also with federal, state, and local emergency response community. Next slide.

RIFT has applicability to a wide range of flood applications, and we recognize there are many agencies that have interest in the movement of water. Our particular interest is in the characterization of water that exists in the flood plain, so outside the main channel, that had the potential to interact with infrastructure systems. And in this context, we've applied this to many types of flood events, including extreme precipitation, such as, what we frequently look at is rainfall associated with hurricanes. Dam failure, spring runoff, tsunamis, and topic today, we've been looking at post-fire runoff. And I'll give a couple of examples of that. Next slide.

I mentioned that we've made some intentional choices about the data we use in RIFT. We prioritize data sets that are, as I said, readily available and publicly available. And we choose data sets to minimize model building time. We also search for data sets that have CONUS scale applicability, but we'll supplement that with information that may be a local scale when necessary to improve prediction and characterization. I show a list of data sets here that we primarily use in that table. And I won't go into detail, but just generally state that the foundational information requires topographic information, available from USGS. There are a number of other data sets of use to help initiate types of flood events, but water would be by far the most essential for us. Next slide.

Our RIFT simulations develop a variety of data sets that can be used in subsequent analyses, such as impact analyses, if you want to do cascading effects, such as contingency simulations, which we've heard about today. At its core, what RIFT produces is high resolution spatial temporal representations of flood depth and velocity. Based on those two types of information, we derive a number of other data sets are useful for these cascading impact analyses. These include looking at things like maximum depth, shown on the top right, which is—really, it's a summary product of the depth and extent, the peak depth and extent, regardless of when it occurred. We can also look at flood wave arrival times. That may be important for response efforts. And duration. And other things, like looking at, how long will water remain in certain locations, and looking at flood dry time. Next slide.

So, the primary use of RIFT has really been to support or enhance situational awareness during extreme events. As I mentioned, a couple of weeks ago, we do this through a combination of real-time simulations and access to archive simulations. We're generally able to provide situational awareness to any event in, depending on what it is, a few minutes to a few hours.

Obviously, response timelines can be hectic, which is what is intended to be shown here in the illustration timeline figure, here. But while it's hectic and exhausting and even stressful, there is reward in providing situational awareness that really can improve response across the nation. Next slide.

All right. So, the specific fire connection here. So, obviously fires can and do have a pretty dramatic effect on the landscape. And really looking at the vegetation cover and potentially even the soil structure when this can occur or last over a period of time. All this really can result in an inability to withhold or attenuate the water that hits the surface, which has the potential to increase volume and velocity of runoff, leading to erosion and other things like flooding.

So, we have the ability to reflect these landscape changes in RIFT. And it's typically done through ways in which we characterize the infiltration processes and other parameters, like surface roughness parameters. We characterize these parameters and changes using a combination of things, like ground-based or satellite-based burn severity and vegetation surveys, such as the information you might get from the burned area emergency response team post fire.

So, a modeling platform like RIFT provides a simulation test bed that allows you, then, to identify areas of high impact consequences. And you can do that through comparisons of pre- and post-fire event analysis. The things we might look for, for example, are areas of previously undefined flood risk. So, you weren't in a flood risk zone prior to the fire, but how does that change post-fire? And areas for high potential for erosion, by looking at things like changes in velocities?

So, the simulations can be used to identify mitigating actions that you might want to take to restore watersheds to optimize protection and restoration, really at that wildland urban interface. Next slide.

So, over the next two slides give a couple of examples. First, this is a look at some post-fire simulations completed up to the Las Conchas fire in New Mexico a little while ago. This one is of particular interest to me, since I was evacuated from the fire, and it came within a few feet of my office in Los Alamos. We simulated, in this case, designed storm events, and we are looking at 50-year, 100-year events. We use burn severity estimates to parameterize post-fire conditions, and then we were able to compare those pre fire conditions.

From the time series chart here, you can really see some pretty drastic changes in both the timing of the peak flow and the magnitude of the peak flow. In this case in particular, a 50-year rainfall event post-fire becomes much more significant, in terms of magnitude, than a 100-year event pre-fire. Extremely intense rainfall in this location, in particular, is of interest because of the frequency of monsoonal driven rains. So, high potential for these types of events. Next slide.

So, this event is a little more recent. We were asked by our colleagues in region eight to help characterize post fire effects from the Cameron Peak fire in Colorado, which occurred last year and burned more than 208,000 acres. Similar to the last example, we were interested in characterizing pre- and post-fire runoff. This time, considering 100-year events over six hour periods, we see similar effects: early peaks, higher magnitude. So, while for this particular location, we didn't see drastic changes in flood extents due to the channelized nature of regions we were looking in, we did identify localized areas of increased flood. So, an example that's shown here in the middle. A neighborhood that didn't previously have any known flood risk that may be at flood risk over the next few years until the vegetation grows back. Next slide.

These were a couple of examples of how RIFT can be used to support response and recovery efforts. We have a lot of experience doing this for a wide variety of events. I'll just briefly mentioned one of the ongoing developments that we had with RIFT is to take this and automate all of our types of simulations in the cloud environment, really to facilitate response time, but also the interactions that we have with the response community. Next slide.

Of course, there's a team that works on RIFT and run RIFT. And if we have the pleasure to work with you, you'll probably meet some of these who run the simulations. Think that's it. Thank you.

MEREDITH BRASELMAN: David, thank you so much. Thank you to all of our panelists and Senator Wyden. This was really great information, and so good to hear what everyone is doing. We do want to take a few minutes here. We've got about nine minutes left here to take some questions. Please continue to submit your questions. Before we jump in, though, we want to conduct one more poll. This time, we'd like to know, based on what you've heard during today's webinar, do you plan to talk to DOE or National Lab about technologies to help mitigate wildfires?

So, while you all are answering that poll, we are going to go ahead and get started on some questions. Let's see. The first question is going to be for Xiaoyuan. How does DCAT compare with tools with simulation capabilities, such as PSSE, PSLF, which can also build and run contingency lists?

XIAOYUAN FAN: Thank you. For this question, DCAT fills in the gap of the hybrid steady state and dynamic simulation. And the whole process is fully automated and backed up by powerful computational schemes. It's also augmented with interconnection wide production models, remedial action schemes. And DCAT can provide corrective action in between different simulated contingencies and stages. And also, along with the database and the visualization modules which I've shown in today's presentation.

I also want to highlight that DCAT team has been actively engaging with the industry. So, our collaborators include Siemens, General Electric—who are actually the vendors of the mentioned two commercial tools in this question. I am proud to say DCAT is a fully compatible with PSSE and the PSF. So far, we have many research papers published and a thorough technical report with software logics and example test cases inside that report, and also published online. Feel free to contact me if you want to learn more about DCAT. Thank you.

MEREDITH BRASELMAN: Thank you so much.

Mark, the next question is for you. Wildfire is heavily dependent on wind. And how much does forest thinning help or not? And does the tool analyze these conditions?

MARK WIGMOSTA: I'll start with the second question first. Yes, we do factor wind into the analysis. And, in terms of how effective thinning is. What we're trying to do with the thinning on the wildfire side is really to reduce flame length by removing some of these ladder fuels that can carry, that generate these higher flame lengths and that can carry that fire up into the crown. And then also some thinning of small diameter trees. So, really what we're doing is reducing the risk of extreme fire behavior.

So in general, it will be a significant improvement over no thinning. Everything's location dependent, but maybe I'll kind of leave it at that. And I will also say that this can also help with suppression efforts. You're much more likely to be able to hold a fire line, particularly if you can keep the fire out of the crown. So, the general answer, I would say, is it is, in general, effective to reducing extreme fire behavior. And again, we do consider wind speed direction, which is a critical part of this fire behavior.

MEREDITH BRASELMAN: Thank you, Mark.

Qing, the next question is for you. Does your risk model predict the number of forest fire events or size of forest fire or maybe both?

QING ZHU: Sorry, it doesn't. It predict the probability of a fire, whether it will occur over a specific region at a particular time point. It's a probability prediction.

MEREDITH BRASELMAN: All right. Thank you so much.

Andre, we've got several questions here on radar. Can the radar tool process the image data from drones and airplanes? And is the radar tool commercial, open source, and is anyone using it?

ANDRE COLEMAN: OK. So, I guess the answer to the first part of the question, as to whether RADR can make use of drone or aircraft-based data, absolutely. So, the whole suite algorithm around there is really designed to make use of lots of different sensor types. And, in fact, where we're currently integrating even more nontraditional sensor types into there. Social media and other kinds of things in there. So, a lot of this is really going to depend, too, on the event. So, a lot of the drone-based imagery is regular RGB imagery, similar to what your phone might capture in a picture. So, that's where we can make use of some more kind of deep learning methods to pick up on objects on the ground. A lot of the satellite imaging is really relying on more imagery from the infrared space, so that we can get through and see through the smoke column.

So, as far as the commercial or open-source question, RADR was originally funded out of a DHS science and technology project. And then was later moved into, actually, DOE's Office of Electricity with the ISER group, which is the Infrastructure Security and Energy Restoration group. And now moved on to DOE CESER. And so, we do use RADR operationally with that group, and we often get requests from utilities for specific needs for various events around the country.

So, the fire part of the work was funded by the DOD JAIC, and they have authorized the release of the code around all the wildfire. So, the plan here is to open source the whole toolset, including the cloud-based architecture and all the algorithms that we're running and using for the wildfire detection. For other parts of the RADR toolbox, if it's a government entity, there's no problem in making that shareable for more commercial entities that are looking to adopt those algorithms into their own softwares and things. That does follow a more of a commercialization path.

MEREDITH BRASELMAN: Thank you so much.

Bill, this next question is for you. Do you have a sense of how likely it might be for an area that burned in the recent past to burn again, or how long that process might take? If an area burned five years ago, is it likely to burn again this year?

WILLIAM RILEY: Right, so, that's an excellent question. I can give a couple of quick thoughts. One is, in order to predict the vegetation succesional trajectories, one needs a model to do that. And DOE is developing several of these types of models. I'll give you a quick example. We had a paper that just came out a year and a half ago, or so, in Nature Climate Change, where we looked at the role of fire and successional trajectories, and then, how those trajectories affected subsequent fire. And it's a complicated problem. Because in some systems the trajectories are limited by nutrient availability, for example. In others, they'll be controlled by light availability and competitive interactions in the canopy. And, in that study, we found the transition from an evergreen forest to a more deciduous forest led to a future reduction in the likelihood of fire. Just because those trees have lower flammability, in general. If you're transitioning from tree-dominated system to a savanna or a grassland, those types of dynamics are also really complex to represent.

And so, the thing I wanted to mention is that DOE is developing a model called FATES, which is integrated into its global model, the E3SM model. But can also be applied at high resolution and there are people here at Berkeley Lab that are leading that effort and applying that modeled structure in California to look at these successional trajectories and how they affect fire likelihood and severity, et cetera.

MEREDITH BRASELMAN: Very good. Thank you so much. Thank you so much to all of our speakers for your time and energy this afternoon. We are at time. Today's information, the presentation, and the recording will be posted on the wildfire website, as will be the rest of the series information sometime in the next week. Ladies and gentlemen, thank you so much for joining us today. And throughout the series this month, we appreciate your questions, your interest, and your follow-up with our speakers. So, while this ends this webinar series, we know there is so much more to discuss. So, please continue to connect with all of our speakers moving forward. Their contact information is in the posted presentations. Thank you again, and have a wonderful day.