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24-12016

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PUBLIC UTILITIES COMMISSION OF NEVADA
Docket No. 24-12016
First Amendment to the Joint Natural Disaster Protection Plan

Prepared Direct Testimony of
Percival Lucban on behalf of the
Regulatory Operations Staff

1. Q. **Please state your name, occupation, and business address.**

A. My name is Percival Lucban. I am a Regulatory Engineer for the Regulatory Operations Staff ("Staff") of the Public Utilities Commission of Nevada ("Commission"). My business address is 9075 West Diablo Drive, Las Vegas, NV 89148.

2. Q. **Does Attachment POL-1 summarize your professional background?**

A. Yes, it does.

3. Q. **What is the purpose of your testimony?**

A. The purpose of my testimony is to provide Staff's recommendations regarding the Joint Application of Nevada Power Company d/b/a NV Energy ("Nevada Power") and Sierra Pacific Power Company d/b/a NV Energy ("Sierra," and together with Nevada Power, "NV Energy") for approval of their First Amendment to the Joint Natural Disaster Protection Plan. Specifically, I address NV Energy's requests for its Situational Awareness program and its mapping corrections related to wildfire tiers. Furthermore, I briefly address NV Energy's portfolio of technologies used for the NDPP.

4. Q. **What are your recommendations to the Commission regarding the issue(s) outlined in Q&A 3?**

A. I recommend that the Commission:

1) Approve NV Energy's requested budget for new weather stations and wildfire cameras, but with the following directive: NV Energy shall file (a) an analysis for optimizing the placement of weather stations and wildfire cameras; and (b) an action plan for implementing the results of that optimization by its next

NDPP triennial plan, or in a future NDPP amendment or NDPP progress report filed before its next NDPP triennial plan.

2) Direct NV Energy to file an analysis of its entire portfolio of technologies in its next NDPP planning docket or NDPP progress report.

3) Approve NV Energy's request to resolve geographic information system mapping gaps in the Mt. Charleston Tier 1 Area and the Lake Tahoe Tier 2 Area.

I. Recommendation No. 1: Approve NV Energy's requested budget for new weather stations and wildfire cameras, but with the following directive: NV Energy shall file (a) an analysis for optimizing the placement of weather stations and wildfire cameras; and (b) an action plan for implementing the results of that optimization by its next NDPP triennial plan, or in a future NDPP amendment or NDPP progress report filed before its next NDPP triennial plan.

5. Q. Please summarize NV Energy's weather station request.

A. Presently, NV Energy has a network of 65 weather stations that are deployed throughout the state, including 59 in its northern service territory and six in the south. During its second triennial NDPP, NV Energy did not propose any capital expenditure in this category on the basis that they would continue monitoring and assessing the current stock of assets before asking for additional funding. In the immediate Docket, NV Energy is requesting funding for an additional 50 weather stations with 45 deployments in the north and five in the south.[1] NV Energy is seeking approval for an additional $303 thousand in OMAG and $1.1 million for its capital budget.[2] NV Energy states that there is a forecasted reduction in both the Situational Awareness capital and OMAG budgets which they were able to realize through lower vendor costs, purchasing efficiencies, and installation efficiencies.[3]

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1 Refiled Application at 17 of 337, at Section 2.3.
2 Refiled Application at 18-19 of 337, at Tables 9 and 10.
3 *See* Attachment POL-2, NV Energy's Response to Staff DR 55.

6. Q. **Please summarize NV Energy's fire camera request.**

A. Presently, NV Energy has 19 long-range and five short-range wildfire cameras installed.[4] In the immediate Docket, NV Energy is requesting funding for an additional 30 long-range wildfire cameras, three long-range mobile cameras, and 20 short-range cameras.[5,6] NV Energy is seeking approval for an additional $593 thousand in OMAG and $997 thousand for its capital budget.[7]

7. Q. **What is likely driving the cost increases of these two programs?**

A. In Docket No. 23-03003, the Commission approved the conversion of a significant portion of the wildland urban interface to Tier 1 (its lowest risk tier) in which NV Energy assets reside.[8] Further, in Docket No. 24-07003, NV Energy filed its NDPP progress report which included enhancements made to the Public Safety Outage Management ("PSOM") plan and seasonal protection settings, among other areas.[9] Given the addition to the NDPP topography and the changes to PSOM and de-energization, it appears that NV Energy seeks to expand its weather stations and wildfire cameras to these areas to enhance data collection and monitoring in addition to filling necessary gaps in Tier 3, Tier 2, and Tier 1-elevated ("1E") Areas.[10] NV Energy is in the process of finalizing the specific locations and tier designations for

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[4] *See* Docket No. 24-08030, Second Report of Nevada Power Company d/b/a NV Energy and Sierra Pacific Power Company d/b/a NV Energy on the progress of its Natural Disaster Protection Plan for the Action Plan Period 2024-2026 regarding all approved projects and programs, at Section 2.1.1.

[5] Refiled Application at 17 of 337, Section 2.3.1.2.

[6] Refiled Application at 226 of 337. Short-range cameras serve a secondary purpose as weather stations.

[7] *Supra* footnote 2.

[8] *See* Docket No. 23-03003, Joint Application of Nevada Power Company d/b/a NV Energy and Sierra Pacific Power Company d/b/a NV Energy for approval of their Joint Natural Disaster Protection Plan for the Period 2024-2026, Commission's August 28, 2023, Order at 26-29. The Commission directed NV Energy to file its revised budget for the second triennial NDPP accounting for the adjustments made pursuant to the August 28, 2023, Order. While these adjustments resulted in a reduction of approximately $42 million from the NDPP's capital budget, there was no change to its OMAG budget. As part of its OMAG budget in the second triennial NDPP, NV Energy included (and the Commission ultimately approved) the resource costs for each of the six major NDPP program areas, including its Inspections, Patrols and Corrections, Vegetation Management, and Situational Awareness programs. NV Energy had budgeted a significant portion to the Tier 1 Area, including approximately 18 percent for vegetation management and 15 percent for inspections, patrols and corrections, with NV Energy aiming to maintain a four-year cadence for the latter.

[9] *See* Docket No. 24-07003, First Report of Nevada Power Company d/b/a NV Energy and Sierra Pacific Power Company d/b/a NV Energy on the progress of its Natural Disaster Protection Plan for the Action Plan Period 2024-2026 regarding its fire season operating practices.

[10] Refiled Application at 17 of 337, at Section 2.3.

both the new weather stations and wildfire cameras and has not yet determined the final locations.[11]

8. Q. What is the significance of the optimal configuration of these assets?

A. The purpose of a network of weather stations and wildfire cameras is to improve localized forecasting and real-time monitoring of conditions in areas of heightened risk. For example, an optimized placement of wildfire cameras "achieves the maximum fire risk reduction of the target area," given the costs of installing and maintaining wildfire cameras as well as a budget.[12] Fire risk of an area is potentially reduced through wildfire camera monitoring.[13] "The magnitude of risk reduction depends on the effective monitoring range of the camera and the distance between the area being monitored and the location of the camera."[14] "The area covered by a wildfire camera depends on the elevation of its surrounding terrains."[15] The same principles apply to weather stations.

9. Q. Has NV Energy optimized the placement of these assets?

A. No.[16] The efforts of NV Energy to achieve such an optimization are ongoing.[17] Indeed, the current configuration of NV Energy's wildfire cameras (i.e., number, type, infrastructure on which they are installed, etc.) is illustrative rather than definitive.[18] It was developed without the use of "a formal optimization model."[19] To date, NV Energy has not been able to quantify the dollar benefits gained or dollar costs avoided by the configuration of the suggested fire camera placement.[20]

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11 *See* Attachment POL-3, NV Energy's Response to Staff DR 54.
12 *See* Shi J., Wang W., Gao Y., Yu N. (2020) "Optimal Placement and Intelligent Smoke Detection Algorithm for Wildfire-Monitoring Cameras" IEEE Access 8 pages 72326 to 72339 https://ieeexplore.ieee.org/document/9068226 at 72333, last seen on March 25, 2025.
13 *Id.*
14 *Id.*
15 *Id.*
16 *See* Attachment POL-4, NV Energy's Response to Staff DR 15.
17 *Id.*
18 *See* Attachment POL-5, NV Energy's Response to Staff DR 48. *See* also Attachment POL-6, NV Energy's Supplemental Response to Staff DR 14 and its accompanying attachment
19 *Id.*
20 *See* Attachment POL-7, NV Energy's Response to Staff DR 16.

NV Energy has many tools to help optimize configurations of its assets, including analytical investments, such as artificial intelligence.[21] Yet, NV Energy has not provided a related analysis that leverages all available tools, including information from its already-installed weather stations and fire cameras (both owned and operated by the utility or another entity) or other tools that NV Energy has (e.g., Technosylva Wildfire Analyst: FireRisk and FireSim; Technosylva FireSight) or is seeking approval of (e.g., Palantir Foundry and AiDash). NV Energy has not even completed an iterative evaluation of risk mitigation efforts already executed and related impacts.

10. Q. Why is it important to optimize the configurations for these assets?

A. An optimal configuration may, among other things, avoid unnecessary redundancy in areas where coverage exists; identify critical areas in which no coverage exists; and reduce unnecessary installations, operational and maintenance costs, and avoidable re-configurations.[22] Given that these capital and OMAG costs are recovered through charging a special rate to its ratepayers, NV Energy should have to demonstrate that the new weather stations and fire cameras are configured optimally.

11. **Q. Please explain whether Staff has any further concerns with NV Energy's weather station and fire camera request.**

A. No. It is apparent that these assets aid in early detection and analysis. However, Staff cautions the Commission that large deployments of these assets should not occur solely because NV Energy does not have asset densities comparable to California.[23] Instead, the Commission should require NV Energy to complete an analysis of optimal configuration of existing and approved assets and then to show the need for any additional assets afterwards.

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21 *Supra* footnote 16.

22 Anecdotally, Staff and NV Energy coordinated a meeting in response to Staff DR 14 in which NV Energy personnel gave an example of a full installation of a fire camera that was sub-optimally placed on one hill, requiring time and effort to relocate to a new location that was more optimal.

23 *Supra* footnote 16.

12. **Q. What is your recommendation on the weather stations and wildfire cameras?**

A. Staff recommends that the Commission approve NV Energy's requested budget for new weather stations and wildfire cameras, but with the following directive: NV Energy shall file (a) an analysis for optimizing the placement of weather stations and wildfire cameras; and (b) an action plan for implementing the results of that optimization by its next NDPP triennial plan, or in a future NDPP amendment or NDPP progress report filed before its next NDPP triennial plan.

II. <u>Recommendation No. 2: Direct NV Energy to file an analysis of its entire portfolio of technologies in its next NDPP planning docket or NDPP progress report.</u>

13. **Q. Does NV Energy have a portfolio of technologies?**

A. Yes. NV Energy has a total of 12 technologies (i.e., NV Energy weather stations; long- and short-range wildfire cameras; fuel moisture sampling; publicly available weather/climate/fuels observations and forecasts; Technosylva Wildfire Analyst: FireRisk and FireSim; Technosylva FireSight; high-resolution WRF weather modeling; CloudFire Fire Weather Dashboard; Pyrecast Weather and Wildfire Forecasts; Microsoft Azure Data Lake and Machine Learning Tools; Palantir Foundry; and AiDash).[24,25]

14. **Q. Is it vital for NV Energy to optimize its portfolio of technologies?**

A. Yes.[26] Across the 12 technologies mentioned above, nine of them are for the analysis of historical data; 11 of them are for conducting real-time assessment; nine of them are for conducting 1-5 day planning; seven of them are for conducting week-ahead planning; four of them are for conducting months-ahead planning; and three of them are for conducting years-ahead planning.[27] Clearly, there is a high risk of overlap or duplication across NV Energy's 12 technologies.

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[24] *See* Attachment POL-8, NV Energy's Supplemental Response to Staff DR 21.

[25] Staff witness Mr. Gaurav Shil addresses the Palantir Foundry and AiDash pilots proposed by NV Energy for approval at his Recommendation No. 2.

[26] *See* Attachment POL-9, NV Energy's Response to Staff DR 20.

[27] *Supra* footnote 24.

Staff is aware that NV Energy is still gaining momentum in identifying and using the appropriate technologies for NDPP. Nevertheless, Staff is concerned that there could be unnecessary duplication of technologies. At the next NDPP planning docket or progress report, Staff is keen to see an effort by NV Energy to review its portfolio of technologies, identify gaps or overlaps, and adjust the number or type of technologies accordingly.

15. Q. What additional information should be included as part of NV Energy's analysis of its portfolio of technologies?

A. Staff suggests that such an analysis should include at least the following: 1) current use cases, 2) future use cases, 3) future cost of implementation for next triennial period, 4) targeted sunset date as applicable with Foundry and AiDash implementation, and 5) next analysis date based on the continued use cases. Staff is willing and able to work with NV Energy to specify the scope of its analysis.

16. Q. What is your recommendation with regards to NV Energy's portfolio of technologies?

A. Staff recommends that the Commission direct NV Energy to file an analysis of its entire portfolio of technologies in its next NDPP planning docket or NDPP progress report.

III. Recommendation No. 3: Approve NV Energy's request to resolve geographic information system mapping gaps in the Mt. Charleston Tier 1 Area and the Lake Tahoe Tier 2 Area.

17. Q. Briefly explain NV Energy's request to resolve two separate geographic information system ("GIS") mapping gaps.

A. As stated in the First Amendment, NV Energy is requesting modifications to its existing fire tier maps that were previously approved by the Commission in Docket No. 23-03003.[28] The map issue was identified by an NDPP team executing hazardous

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28 Refiled Application at 215 of 337.

ground fuels and tree trimming work.[29] The team found that a Tier 1 area was non-contiguous in several areas.[30] This concern was also expanded into a review of the approved fire tier maps which informed NV Energy of the mapping corrections being requested in the First Amendment.[31] NV Energy claims that these modifications are necessary to correct errors in the previously approved maps.[32] Currently, NV Energy is not requesting additional funding to address these changes.[33] Rather, the work for these areas will be prioritized among other planned work such as patrols and inspections, vegetation management, and assessments for conversion to a covered conductor alternative where applicable.[34] To date, NV Energy has already expended a total of approximately $94,000, in NDPP funding for pole grubbing and right-of-way clearing for the Steamboat 212 circuit despite the lack of Commission approval of the mapping corrections.[35,36]

18. Q. Given the GIS mapping gaps identified, please explain whether there are any controls in place that would ensure NV Energy's identification of the fire tier area maps are recorded and submitted in an NDPP or NDPP amendment appropriately.

A. NV Energy intends to draft procedures around risk map creation and updates that will include a quality assurance review, operational review, and communication for any changes to the fire tier boundaries.[37]

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29 *See* Attachment POL-10, NV Energy's Response to Staff DR 18. *See also* Attachment POL-11, NV Energy's Response to Staff DR 59.

30 *Id.*

31 *Id.*

32 *See* Prepared Direct Testimony of Danyale Howard at Q&A 45.

33 *Id.*

34 *Id.*

35 *See* Attachment POL-12, NV Energy's Response to Staff DR 56.

36 Here, Staff is not contesting the estimated $17,300, and $76,700, expended in 2023 and 2024, respectively. Regardless of the mapping corrections, mitigating wildfire risk in a timely manner is the right thing to do. However, Staff would recommend that the Commission to take notice of the fact that NV Energy did not discover these mapping corrections until 2024 even though they had been existing since 2019. Therefore, NV Energy should bring these types of corrections in any aspect of the NDPP in front of the Commission in an expeditious manner and not wait for more than five years as was the case here. Staff is in the process of reviewing the 2024 expenditures that are before the Commission in NV Energy's NDPP Cost Recovery in Docket No. 25-02032.

37 *Supra* footnote 29. NV Energy's Response to Staff DR 18.

19. Q. **Please explain whether NV Energy expects further mapping corrections to be filed in the context of another amendment to the current triennial plan.**

A. NV Energy does not expect further mapping corrections to be filed in the context of an amendment to the current triennial plan.[38] However, in preparation of its next triennial NDPP, NV Energy will evaluate the industry standard for updating or revising the risk prioritization for areas where past risk mitigation efforts have been executed, which may indicate a need for future revisions to the fire tier maps.[39]

20. Q. **Please explain whether Staff has any concerns with NV Energy's mapping corrections.**

A. While Staff has no concern with addressing the gaps through its inclusion here, NV Energy has already expended NDPP funds and further intends to spread its remaining budgets to mitigate risk in these areas through a reprioritization of existing NDPP programs, which in turn may reduce the approved funding available in areas that were approved in the second triennial NDPP. Currently, there is a program-wide, forecasted OMAG underspend of approximately $14.8 million and a program-wide, forecasted capital underspend of approximately $11.4 million across the two service territories.[40] Consequently, the potential of another amendment requesting additional funding is probable once NV Energy catches up in programs that are currently forecasted to be underspent. If these additional areas are approved by the Commission, there would be NDPP work to be performed under vegetation management, fire tier patrols, inspections and corrections, and the non-expulsion fuse replacement.[41] While NV Energy has not yet developed a work schedule or cost forecast for the work in these additional areas, the only immediate work could occur in 2026 for the annual line

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38 *Id.*

39 *Id.*

40 *See* Attachment POL-13, NV Energy's Response to BCP 1-02, *and see also* Attachment POL-14, NV Energy's Response to Staff DR 09.

41 *See* Attachment POL-15, NV Energy's Response to Staff DR 53.

patrol of the new Tier 2 area in Lake Tahoe, which is estimated to be approximately $1,100.[42]

21. Q. What is Staff's recommendation regarding NV Energy's request to resolve the GIS mapping gaps in the Mt. Charleston Tier 1 Area and the Lake Tahoe Tier 2 Area?

A. Staff recommends that the Commission approve NV Energy's request to resolve the GIS mapping gaps in the Mt. Charleston Tier 1 Area and the Lake Tahoe Tier 2 Area.

22. Q. Please summarize your recommendations.

A. I recommend that the Commission:

1) Approve NV Energy's requested budget for new weather stations and wildfire cameras, but with the following directive: NV Energy shall file (a) an analysis for optimizing the placement of weather stations and wildfire cameras; and (b) an action plan for implementing the results of that optimization by its next NDPP triennial plan, or in a future NDPP amendment or NDPP progress report filed before its next NDPP triennial plan.
2) Direct NV Energy to file an analysis of its entire portfolio of technologies in its next NDPP planning docket or NDPP progress report.
3) Approve NV Energy's request to resolve geographic information system mapping gaps in the Mt. Charleston Tier 1 Area and the Lake Tahoe Tier 2 Area.

23. Q. Does this conclude your testimony?

A. Yes, it does.

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42 *Id.*

QUALIFICATIONS OF
PERCIVAL O. LUCBAN

WORK EXPERIENCE

PUBLIC UTILITIES COMMISSION OF NEVADA
Las Vegas, NV
Regulatory Engineer, November 2011 to Present

Responsibilities include evaluating and providing testimony for electric resource plans, general rate cases, and smart grid technologies.

NV ENERGY
Las Vegas, NV
Telecommunications Engineer, July 2010 to November 2011

Performed advanced level design, implementation and maintenance tasks associated with large, complex and cost effective voice and data processing applications and networking solutions. Provided recommendations for improvements on telephony systems and other voice/data networks. Recommended and established telecommunication installation and material standards. Provided project management and coordination for major projects through completion while tracking expenditures against Operations/Maintenance and capital projects. Provide technical support on all escalated maintenance issues and/or non-compliance issues.

NV ENERGY
Las Vegas, NV
Regional Electric Engineer, January 2008 to July 2010

Responsibilities included project management of distribution capital budget and renewable energy projects for the South Las Vegas District, identifying system improvement opportunities for capital maintenance, providing engineering support for the Distribution Design process, investigating and resolving existing power quality problems, conducting economic and technical distribution studies, and defending through the annual distribution construction budget in accordance with corporate guidelines and timetables.

NV ENERGY
Las Vegas, NV
Metering Engineer, April 2007 to January 2008

Provided engineering support to technical crews. Provided technical engineering support and interpretation on electrical service requirements.

EDUCATION

UNIVERSITY OF NEVADA, LAS VEGAS
Las Vegas, NV

Bachelor of Science received from the Department of Electrical Engineering – Dec 2006

NV Energy

RESPONSE TO INFORMATION REQUEST

DOCKET NO:	24-12016	**REQUEST DATE:**	03-13-2025
REQUEST NO:	Staff 55	**KEYWORD:**	Table 9 OMAG & Table 10 Capital
REQUESTER:	Lucban	**RESPONDER:**	Hoon, Alexander (NV Energy)

REQUEST:

Reference: Section 2.3 Situational Awareness, Tables 9 and 10

Question: Table 9 in the Amendment provides a budget summary for Situational Awareness - OMAG for Nevada Power and Sierra. Table 10 in the Amendment provides a budget summary for Situational Awareness - Capital for Nevada Power and Sierra. Given these tables, please answer the following:

1. With respect to Table 9, Situational Awareness - OMAG, please explain in detail the ($24,555) reduction identified for Nevada Power. As part of this response, explain whether the currently approved work is incomplete, if the costs to complete the currently approved work is under budget, etc.

2. With respect to Table 9, Situational Awareness - OMAG, please explain in detail the ($202,876) reduction identified for Sierra. As part of this response, explain whether the currently approved work is incomplete, if the costs to complete the currently approved work is under budget, etc.

3. With respect to Table 10, Situational Awareness - Capital, please explain in detail the ($100,000) reduction identified for Sierra. As part of this response, explain whether the currently approved work is incomplete, if the costs to complete the currently approved work is under budget, etc. Please contact Percy Lucban with any clarification questions pertaining to the above request.

RESPONSE CONFIDENTIAL (yes or no): No

TOTAL NUMBER OF ATTACHMENTS: None

RESPONSE:

1. The ($24,555) forecast reduction in 2024-26 OMAG for Nevada Power cost savings realized in 2024 during implementation of currently approved situational awareness initiatives.

At present, the currently approved work is either completed or proceeding within budget expectations, with some subscription costs coming in lower than originally forecasted due to negotiated vendor agreements.

The First Amendment represents an updated, more accurate reflection of expected ongoing costs based on current contract terms and operational experience.

2. The ($202,876) forecast reduction in 2024-26 OMAG reduction for Sierra is primarily due to cost savings realized in 2024 during implementation of currently approved situational awareness initiatives.
At present, the currently approved work is either completed or proceeding within budget expectations, with some subscription costs coming in lower than originally forecasted due to negotiated vendor agreements.

The First Amendment represents an updated, more accurate reflection of expected ongoing costs based on current contract terms and operational experience.

3. The ($100,000) reduction in forecasted 2024-26 capital costs for Sierra reflects better-than-expected pricing for certain wildfire cameras in 2024. As procurement activities progressed, purchasing efficiencies helped to lower the cost of wildfire cameras below initial estimates. This was mainly due to the acquisition of 5 cameras by SPPC in western Nevada that were going to be decommissioned. NV Energy was able to acquire these cameras at a reduced capital cost.

Additionally, some site-specific installation requirements were less extensive than anticipated, through our partnerships with government agencies, reducing total capital. The Minden Camera was installed on an AT&T tower at the Douglas County Sheriff's Office, which resulted in a reduced cost to ratepayers.

Importantly, this reduction does not indicate any reduction in the number of assets to be deployed or in the overall program goals—rather, it reflects NV Energy's effort to manage ratepayer funds prudently and efficiently.

NV Energy

RESPONSE TO INFORMATION REQUEST

DOCKET NO:	24-12016	**REQUEST DATE:**	03-13-2025
REQUEST NO:	Staff 54	**KEYWORD:**	Breakdown of Capital and O&M Costs
REQUESTER:	Lucban	**RESPONDER:**	Hoon, Alexander (NV Energy)

REQUEST:

Reference: Section 2.3 Situational Awareness Improvements

Question: Please provide a breakdown of the capital and O&M costs associated with the 50 weather stations and 53 fire cameras NV Energy is requesting additional funding for, by service territory and tier. For the fire cameras, please specify the type of camera and identify the type of infrastructure they would be placed upon. Please contact Percy Lucban with any clarification questions pertaining to the above request.

RESPONSE CONFIDENTIAL (yes or no): No

TOTAL NUMBER OF ATTACHMENTS: None

RESPONSE:

At this time, NV Energy is in the process of finalizing the specific locations and tier designations for both the 50 weather stations and 53 wildfire cameras. Final locations will be determined in coordination with external partners, including the University of Nevada, Reno Seismological Lab and the Bureau of Land Management, to ensure optimized coverage and to avoid redundancy with other camera installations. Weather stations will be determined in coordination with the National Weather Service.

The breakdown by service territory will be as described in Section 2.3.1 and 2.3.2 in the First Amendment (page 17):
50 weather stations (45 SPPC, 5 NPC)
30 long-range wildfire cameras (25 SPPC, 5 NPC)
3 mobile long-range cameras (2 SPPC, 1 NPC)

20 short-range cameras (10 SPPC, 10 NPC)

While NV Energy is not yet able to provide a finalized breakdown by tier and type of infrastructure to be installed on, NV Energy provides estimated unit costs and types of equipment, based on recent procurement data and projected installations:

Estimated Unit Costs:

• Weather Stations (installed on NVE infrastructure) -- unit cost ~$22k for instrument and installation and ~$4K ongoing subscriptions and maintenance per year.

• Long Range Camera (installed on NVE infrastructure) -- unit cost $20k for camera and installation and $6K ongoing subscriptions and maintenance per year.

• Long Range Camera (installed on Wireless Internet Service Provider infrastructure) -- unit cost $13k for camera and installation and $12k ongoing subscriptions and maintenance per year.

• Mobile Camera -- unit cost $60k for camera and installation and $3k ongoing subscriptions and maintenance per year.

• Short Range Camera (installed on NVE infrastructure) -- unit cost $12.5k for camera and installation and $2k ongoing subscriptions and maintenance per year.

NV Energy

RESPONSE TO INFORMATION REQUEST

DOCKET NO:	24-12016	**REQUEST DATE:**	01-14-2025
REQUEST NO:	Staff 15	**KEYWORD:**	Fire Camera Configuration
REQUESTER:	Macatangay	**RESPONDER:**	Hoon, Alexander (NV Energy)

REQUEST:

Reference: page 32 of 313

Question: The Narrative says that "[t]he suggested fire camera placement for this request includes: 30 long-range wildfire cameras, with 25 placed in the North and five in the South; Three long-range mobile cameras, with two placed in the North and one placed in the South; 20 short-range cameras, with 10 placed in the North and 10 placed in the South" (see page 32 of 313). Did NV Energy develop or apply quantitative tools seeking to optimize the configuration (i.e. location, size, features, capabilities, etc.) of the "suggested fire camera placement"?

A.If no, please explain why.

B.If yes, please address the following.

i.What is the literature supporting the methodology NV Energy used to seek the optimal configuration (i.e. location, size, features, capabilities, etc.) of the "suggested fire camera placement"?

Ii.Apart from the Companies, what are the regulated electric utilities (in the US or elsewhere) that have developed and subsequently deployed the methodology in (b)(i)?

Iii.In relation to the regulated electric utilities identified in (b)(ii), did the Companies consult them, or otherwise seek inputs from them, in the process of developing and subsequently deploying the methodology in (b)(i)?

Iv.Kindly provide executable versions of all relevant software files for NV Energy's calculations seeking to optimize the configuration (i.e. location, size, features, capabilities, etc.) of the "suggested fire camera placement," at a level of detail enabling an independent auditor to replicate any calculations from start to end.

C.Please email Manny Macatangay remacatangay@puc.nv.gov for any clarification questions.

RESPONSE CONFIDENTIAL (yes or no): No

ATTACHMENT CONFIDENTIAL (yes or no): No

TOTAL NUMBER OF ATTACHMENTS: Four (Zipped)

RESPONSE:

Yes, NV Energy has a process for using quantitative tools to optimize the configuration of the wildfire cameras.

A. N/A.

B. The Companies are still awaiting further view-shed analysis from the University of Nevada, Reno, which will help NV Energy to optimize locations for the new wildfire camera placement. This will be similar to view-shed analysis that the Companies have done in the past for previous wildfire cameras. See Attachment 01 of the analysis the Companies did for the 2022-23 year. The Companies are also working in collaboration with the Bureau of Land Management (BLM) in Nevada to optimize the placement of these cameras with the placement of BLM cameras to maximize the benefits of camera coverage across the State of Nevada.

There currently are thousands of miles of transmission and distribution lines without visibility from wildfire cameras in the NV Energy service territory, so the Companies are requesting additional funding to install more wildfire cameras to help fill in the gaps of wildfire coverage.

For comparison, as of January 2025, the State of California had 1,144 High-definition, pan-tilt-zoom cameras deployed. These cameras are owned by investor-owned utilities as well as federal and state fire agencies. The total number of cameras in Nevada is 65, of which NV Energy owns 20. The density of cameras in Nevada is only about one-tenth of the density of cameras in California.

California: Approximately 0.70 cameras per 100 square miles.

Nevada: Approximately 0.06 cameras per 100 square miles. ~less than 1/10th the coverage than California.

This comparison shows that California has significantly higher camera density compared to Nevada, likely reflecting the larger investment in wildfire detection infrastructure due to California's more frequent and intense wildfire activity. Nonetheless, the wildfire risk in Nevada is high and the wildfire camera network gaps must be addressed using a solid methodology as described in the answer below.

i. The methodology NV Energy uses to determine the optimal configuration for fire camera placement draws from industry standards, technological capabilities, risk assessment practices, and input from key stakeholders. While specific "literature" detailing NV Energy's exact approach does not exist, the specific methodologies that NV Energy uses to support fire camera placement are detailed below.

1. Wildfire Risk Mapping
a. Use of Federal and State agency risk mapping that assesses wildfire risk based on vegetation, historical fire data, topography, and climate conditions.
b. Use of Technosylva Wildfire Risk Mapping to help guide which areas may have the heightened risk based off historical fire weather events.

2. View-Shed Analysis
a. Geographic Information System techniques and tools such as ArcGIS, which include visibility analysis methods.
b. Application ensures that cameras cover the largest possible area with minimal blind spots, especially in heightened risk areas.

3. Infrastructure Monitoring
a. Stationary long-range and short-range cameras are strategically placed near utility infrastructure to monitor for wildfires in those areas.
b. The three mobile cameras that the Companies are proposing will be available for the Companies to monitor ongoing wildfires and fill in any gaps to monitor such wildfires within short notice.

4. Integration of Weather Station Data
a. Weather's influence on wildfire behavior is well researched and documented.
b. Application ensures that wildfire cameras are paired with weather stations in areas where fire risk increases due to specific weather conditions (e.g., high wind corridors).

5. Artificial Intelligence and Fire Detection Models
a. Literature: There are numerous papers on AI-based wildfire detection, such as "An AI-Based Early Fire Detection System Utilizing HD Cameras and Real-Time Image Analysis" The full text can be found here:
https://ojs.bonviewpress.com/index.php/AIA/article/view/975/709
b. Application: Advanced cameras with AI fire detection capabilities are deployed to areas where early detection is critical.

6. Stakeholder Collaboration
a. Guidelines: Public Utility Commission (PUC) regulations and community input for localized insights to the Natural Disaster Protection Plan.
b. Application: Collaborative input with the Bureau of Land Management and other fire agencies ensures cameras serve both utility and public needs.

7. Cost-Benefit Analyses
a. While direct cost-benefit analyses of ground-based wildfire camera systems are scarce, a study titled "Machine learning estimates on the impacts of detection times on wildfire suppression costs" discusses the potential advantages and disadvantages of such systems. This study explores how prompt wildfire detection, facilitated by machine learning algorithms, can influence wildfire behavior and associated suppression costs. The research underscores the importance of early

detection in designing efficient suppression strategies and suggests that investments in advanced detection technologies can yield substantial cost savings. The paper is attached at Attachment 03, and the full text can be found here:
https://journals.plos.org/plosone/article?id=10.1371%2Fjournal.pone.0313200
b. These studies collectively suggest that investing in advanced wildfire detection technologies, including satellite systems, UAVs, and ground-based cameras, can offer significant economic benefits by enhancing early detection capabilities and reducing suppression costs.
c. Application: Balancing the number and capabilities of cameras with budget constraints.

ii. The industry standard for wildfire cameras for utilities in the western U.S. is guided by the need for early fire detection, situational awareness, and integration with advanced monitoring systems. Several regulated electric utilities in the U.S. and internationally have developed and deployed methodologies for optimizing wildfire camera configurations. These methodologies often leverage Geographic Information Systems (GIS), risk modeling, stakeholder collaboration, and technological advancements as well. The following is a list of utilities with efforts similar to NV Energy's:

1. Pacific Gas and Electric Company (PG&E) – California Methodology:
PG&E uses GIS-based fire-threat mapping and historical fire data to identify high-risk areas. They integrate camera placement with AI to improve detection of smoke and flames. PG&E collaborates with the California Public Utilities Commission (CPUC) to align with wildfire mitigation plans (WMPs). Deployment:
As of 2022, PG&E had installed over 600 wildfire cameras in high-risk areas.
The cameras are integrated into ALERTWest, a public-private partnership that provides data to utilities and emergency responders.

2. San Diego Gas & Electric (SDG&E) – California Methodology:
SDG&E utilizes advanced fire-threat zone mapping and weather modeling.
Their camera placement integrates real-time weather data and AI to optimize coverage in high fire-risk areas. Deployment:
Over 230 cameras are strategically positioned across San Diego County, most of them on AlertWest wildfire camera network. Cameras feed into SDG&E's Emergency Operations Center and are used for real-time decision-making and resource allocation.

3. Southern California Edison (SCE) – California Methodology:
SCE employs a layered approach that combines wildfire risk assessments, community input, and regulatory guidance.
Camera locations are prioritized in areas with frequent fire activity, dense vegetation, and critical infrastructure.
Deployment:
Approximately 200 cameras are deployed in coordination with their wildfire mitigation strategies. These cameras are all on the AlertWest wildfire camera network and also linked with SCE's 1700 weather stations and operational centers.

iii.Yes, NV Energy has had high level conversations with the other regulated electric utilities above about wildfire cameras. The main feedback that NV Energy has received is that more wildfire cameras are needed to adequately and rapidly detect new wildfires in the vicinity of NV Energy facilities, or put succinctly, “you don’t have enough wildfire cameras.” These IOUs also gave feedback that they were “pleased” with services from AlertWest and their Artificial Intelligence Fire Detection. The utilities mentioned above are all a part of the AlertWest Wildfire Camera Network, the same as NV Energy. For comparison of wildfire camera coverage, you can visit www.alertwest.live

iv. NV Energy does not have executable versions of software files for calculations. NV Energy does have a preliminary viewshed analysis from the University of Nevada, Reno, that shows the placement of NV Energy and BLM wildfire cameras across the State of Nevada, overlayed with wildfire occurrence. This preliminary analysis is attached as Attachment 04.

PLOS ONE

RESEARCH ARTICLE

Machine learning estimates on the impacts of detection times on wildfire suppression costs

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Abstract

As climate warming exacerbates wildfire risks, prompt wildfire detection is an essential step in designing an efficient suppression strategy, monitoring wildfire behavior and, when necessary, issuing evacuation orders. In this context, there is increasing demand for estimates of returns on wildfire investments and their potential for cost savings. Using fire-level data from Western Canada during 2015–2020, the paper associates variation in wildfire reporting delays with variation in suppression costs. We use machine learning and orthogonalization methods to isolate the impact of reporting delays from nonlinear impacts of the fire environment. We find that reporting delays account for only three percent of total suppression costs. Efforts to improve detection and reduce wildfire reporting delays by one hour lead to a modest 0.25% reduction in suppression costs. These results suggest that investments in detection systems that reduce wildfire reporting delays are not justified on suppression costs savings alone.

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1. Introduction

Wildfire suppression is a priority for areas in which forests and human communities intersect. In the western Canadian province of Alberta, a forested area spanning 39 million hectares, or the size of Germany, is enjoyed by over one million individuals as home, workplace and places of recreation [1]. While wildfire is an integral component in the boreal forest ecosystem [2], out-of-control fires can have high socioeconomic costs. They force emergency evacuations of people [3, 4] as they threaten the destruction of both human communities and wildlife habitat [5]. Wildfires negatively impact air quality [6], and deteriorate respiratory health more than fine particles from other sources of air pollution [7]. Economic effects are also significant as wildfires can cause an array of direct and indirect losses [8], decrease property values [9], earnings and employment [10].

Towards protecting communities, industries and natural habitats, the Province of Alberta maintains a policy of total wildfire suppression in the Forest Protection Area (Fig 1). The provincial agency, Alberta Wildfire, is tasked with carrying out suppression programs. The programs are designed with the double objective of safeguarding human and environmental assets, while minimizing operational costs as stewards of public funds.

Competing interests: The authors have declared that no competing interests exist.

Fig 1. Alberta's forest protection area. *Source*: Government of Alberta (available online at https://open.alberta.ca/publications/forest-protection-area-map).

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In the recent 20 years, as suppression costs rise with increasingly severe fire seasons in Canada, there has been growing awareness on the impacts and costs of wildfires [11, 12]. In Alberta, devastating fire seasons in 2016, 2019, and 2023 serve as reminders of wildfires' economic and social disruptions. In 2016, the damage caused by the 600 thousand hectare Fort McMurray fire, along suppression expenditures, cost of community relocation, and indirect impacts on the environment, totaled an estimated $10.9 billion. Alberta Wildfire expensed over half a billion in suppression operations; additionally, with $3.6 billion in insured property damage, the fire was the costliest insured natural disaster in Canadian history [13–15]. In 2019, nearly a thousand individual wildfires spread across a cumulative 880 thousand hectares, and the expenditures for their suppression totaled $570 million [1]. Finally, the 2023 fire season is responsible for almost two million hectares of area burned, which amounts to almost twice as much the total area burned from the five previous seasons [16]. After incurring $851 million on fire suppression in 2023 [17], the government opted to designate $2 billion in contingency funds for fire and other natural disasters in 2024 [18].

Future prognostics for the threat of wildfires are not encouraging. Across North America, climate change continues to create extreme fire weather conditions [19–23]. Moreover, governments around the world are increasingly challenged to restrain expenditures to balance the public purse. Consequently, wildfire management agencies such as Alberta Wildfire are embattled in facing more challenging wildfires, while also dealing with increased public scrutiny [24] and uncertain budgets [25].

Towards reducing expenditures on wildfire suppression, management agencies are prompted to consider the role of pre-suppression strategies such as early detection mechanisms. Alberta Wildfire recognizes the importance of early detection; it is one of the last Canadian agencies to keep a large network of manned lookout towers, and also engages regularly with the general public to raise awareness on the importance of public reporting of out-of-control wildfires. Through a coordination of manned and unmanned detection tools, including using remote cameras and unmanned aircraft systems (UAS), the agency strives to reduce the delay between a wildfire's ignition and the time at which the fire is first reported, which we term "reporting delay".

Wildfire detection is central to management and response. The recent and tragic wildfires in Maui, Hawaii, has brought the issue of timely wildfire detection and community alerts to the forefront of the wildfire management debate [26]. Nevertheless, given limited resources, investments into detection systems can crowd out investments into fire prevention and forest management [27]. As a result, it is important to understand how early detection translates into costs savings and other socioeconomic benefits.

In this paper, we estimate the impact of reporting delays on the cost of suppression, controlling for the fire environment. As fire expenses can be very nonlinear on many important characteristics of the fire environment (e.g. weather), we employ nonparametric empirical models where we make no assumptions about the shape of the influence of the fire environment variables on suppression costs. We estimate marginal effects of reporting delays using a Double/Debiased Machine Learning (DML) algorithm [28]. As we further discuss below, the algorithm allows us to maintain the causal interpretation of the impact of reporting delays on fire suppression costs while utilizing flexible Random Forests algorithms to fit nonparametric fire environment functions. Our models are estimated using fire-level data from 2015 to 2020.

The remainder of the paper is organized as follows: Section 2 summarizes Alberta's wildfire detection framework. Section 3 describes the data and presents summary statistics. The empirical model and estimation is discussed in section 4. Section 5 presents the results, and section 6 offers concluding remarks, including a discussion on policy implications.

2. Wildfire detection in Alberta, Canada

Alberta Wildfire has a mandate in protecting, in descending order of priority, human lives, communities, watersheds and sensitive soils, natural resources, and infrastructure. Towards fulfilling this mandate, the Province of Alberta has adopted strategies for both wildfire prevention and mitigation, as well as for active suppression (more details on mandate priorities and protocol found at: https://www.alberta.ca/how-we-fight-wildfires). Year-round prevention efforts includes public education campaigns on safe burning procedures and permitting, while mitigation includes coordinated fuel reduction activities [29], as well as the Province's provision of funding to communities to reduce their wildfire risk through taking part in the FireSmart program (https://www.alberta.ca/firesmart). In addition, regional fire bans are implemented during periods of high fire risk (https://www.alberta.ca/fire-bans), further reducing the likelihood of human-caused fires. In our dataset, we find that 56% of fires are linked with human activities such as littering, poorly controlled waste burning, and off-highway vehicle driving.

Despite the best efforts of Alberta Wildfire and local communities to reduce wildfire risk, ignitions and wildfire spread continues to occur every fire season. When this occurs, Alberta

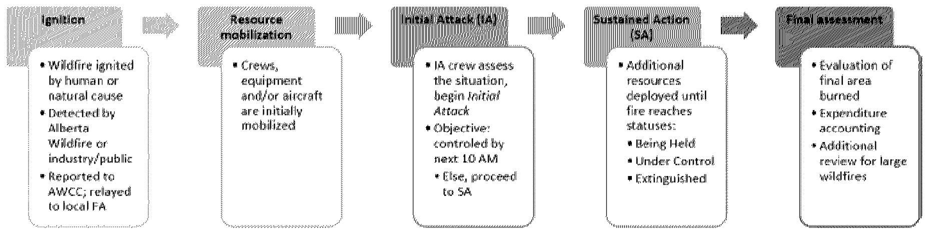

Fig 2. Flowchart of Alberta Wildfire's response protocol.

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Wildfire initiates a response protocol, as summarized in Fig 2. Response begins as soon as a wildfire is detected in the Forest Protection Area, via the agency's detection system or as notified by the public. Having received a notification, the Alberta Wildfire Coordination Centre relays the incident to its respective Forest Area region. Resources are then mobilized to the fire for assessment and suppression action. Suppression is terminated when a lead Incident Commander declares the fire to be extinguished, and crews are demobilized after completing a final assessment of the burn area.

Within this strategic framework, the preliminary stages of detection and reporting are critical, because the early and precise detection of wildfires allows decision makers the necessary time and information to implement an appropriate response. Alberta Wildfire classifies fires in five categories, or classes, based on fire size: A: <0.1 ha; B: 0.1–4 ha; C: 4–40 ha; D: 40–200 ha; E: >200 ha. Fire size is continuously monitored. Upon reaching a particular "size class", a fire will receive certain minimum levels of suppression resources (e.g. crew, equipment and/or aircraft deployed to the fire), as mandated by Alberta Wildfire protocol.

Detection depends largely on regular patrols by Alberta Wildfire crews, as well as on public reporting. In addition, Alberta is one of the last jurisdictions in Canada to keep an extensive network of manned lookout towers. Alberta Wildfire maintains that the towers continue to be critical for precise wildfire detection in a populous wildland-urban interface that covers much of the Forest Protection Area [30].

In addition to traditional detection infrastructure, Alberta Wildfire continues to trial new technologies in order to enhance current detection strategies. In 2021, Alberta Wildfire had invested over $4.3 million in piloting the use of tools such as cameras and unmanned area vehicles, or UAS [30, 31]. This technological renewal sought to improve detection capacity, as well as to help the agency in its resilience to budget shocks that have impacted staffing in recent fire seasons [32]. Infrared imaging via UAS is a highly promising emergent technology, both as an effective wildfire detection tool, and in providing real-time data on fire behavior in areas that are geographically remote or too dangerous for wildland firefighters to access in-person [33–35]. Most recently in 2023, Alberta Wildfire has, for the first time, granted permission for a contractor to fly UAS beyond visual line of sight [36].

3. Data

Our data was primarily sourced from Alberta Wildfire's internal data on operations and expenditure from April 1, 2015 to December 31, 2020. Table 1 shows the distribution of fires, by size class and year.

Table 2 shows our variables, their descriptions, and sources. The majority of our variables are from Alberta Wildfire's data management system, FIRES. Fire-level observations of operations and expenditure data were combined with geospatial data from public databases (Altalis, Government of Alberta GENESIS, Statistics Canada) to create a high-dimensional final dataset

Table 1. Distribution of wildfires by size class, calendar years 2015 to 2020.

Calendar Year	Size class					Total
	A	B	C	D	E	
	(<0.1 ha)	(0.1–4 ha)	(4-40ha)	(40–200 ha)	(>200ha)	
2015†	1089	514	107	44	64	1818
2016	930	414	62	19	11	1436
2017	852	296	52	24	20	1244
2018	824	349	87	18	21	1299
2019	635	272	61	16	21	1005
2020	574	129	16	1	3	723
Total	4904	1974	385	122	140	7525

† Excludes fires from Jan 1 to Mar 31, 2015 (n = 38). Size class is based on the final area burned measured after the fire is extinguished

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with detailed information on suppression costs, reporting delay, and the fire environment. Expenditure values that are originally reported in current year dollars have been set to 2020 dollars to account for inflation.

3.1 Suppression costs and reporting delays

For each fire, the data allow us to calculate the expenditures of: i. operating or renting aircraft and equipment, ii. salaries and wages for wildland fighters directly linked to each suppression

Table 2. Variables definitions and sources.

Variable	Definition	Source
Costs	Suppression expenditure per wildfire (2020 dollars)	FIRES
Reporting delay	Hours of delay between fire ignition and report	FIRES
Fire environment		
Weather	Weather variables are max/min/total on assessment day +/- 2 days	
Temperature	Maximum temperature (˚C)	FIRES
Wind speed	Maximum wind speed (km/h)	FIRES
Rain	Total rainfall (mm)	FIRES
Humidity	Minimum relative humidity (%)	FIRES
Fuel type	DV* for *Timber* or *Slash* fuel types (baseline: *Open* (grass, peat, moss) or *Manmade*)	FIRES
Fire type	DV* for *Crown* fire type (baseline: *Ground* or *Surface*)	FIRES
High elevation	DV* for elevation over 1250 m	Altalis
South aspect	DV* for mean aspect between 157.5–202.5˚	Altalis
Lake/River	DV* for lakes/rivers (within 3km). Surface water can serve as natural boundaries, and can be used to suppress fire.	GeoDiscover

Notes: * DV refers to dummy variables where 1 indicates the presence of the attribute; 0 for absence (or baseline). Data sources are as follows. FIRES: the Alberta Wildfire data management system. We received both publicly available and internal datasets for this project. (Publicly available data is available on www.alberta.ca/wildfire-maps-and-data.aspx). Altalis: a service that stores and publicly distributes the Government of Alberta's comprehensive digital data sets. (www.altalis.com). GeoDiscover: Government of Alberta's database for publicly available geospatial data (formerly GENESIS). Refer to https://geodiscover.alberta.ca/geoportal and open.alberta.ca/interact/geodiscover-alberta.

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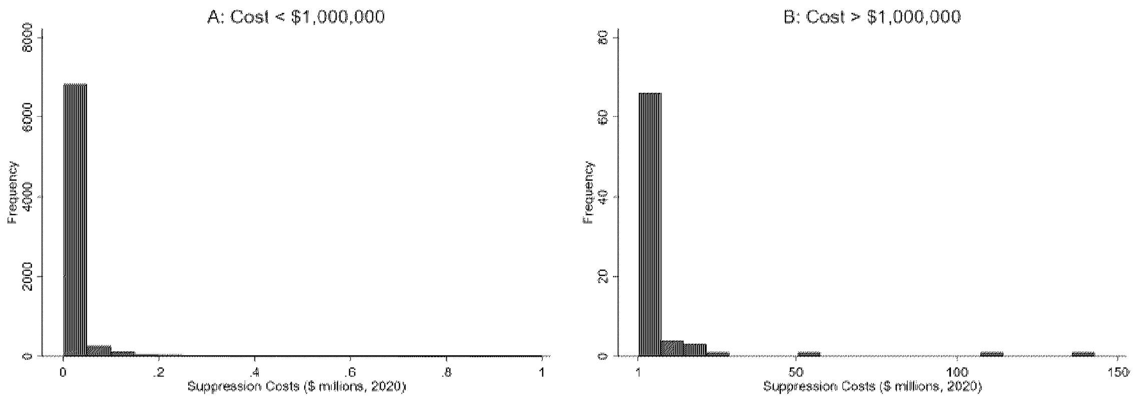

Fig 3. Wildfire suppression cost distribution.

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mission, and iii. associated incidental costs (e.g. providing meals and accommodations for staff on extended deployment).

Empirical modeling of wildfire suppression expenditures is challenging for several reasons. First, the distribution of costs is significantly skewed to the right. Fig 3 shows the cost distribution by splitting the data into two subsamples: less than and more than one million dollars. In both cases, the majority of the data is concentrated on lower cost levels, with a few extreme points.

Even a single extreme wildfire, as is common in recent years, may dominate a sizeable share of annual expenditures, skew the data, and make it challenging to fit wildfire suppression expenditure models. Fig 4 shows the total suppression operation expenditures, by size class, from 2015–2020. As an example of outlier wildfire events, in 2019, the 21 extremely large fires

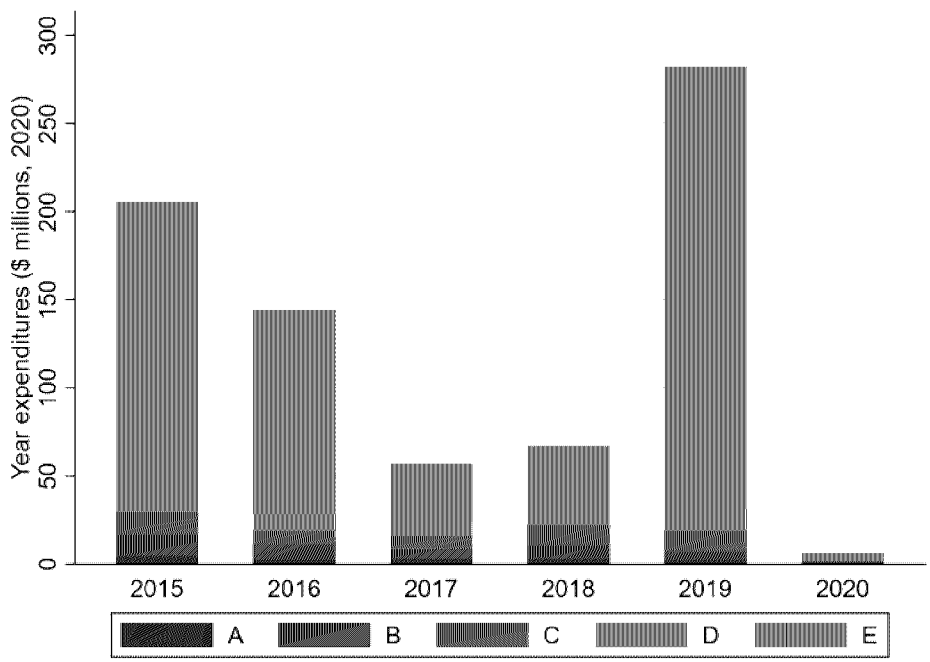

Fig 4. Yearly suppression operation expenditures, by size class (millions of 2020 dollars).

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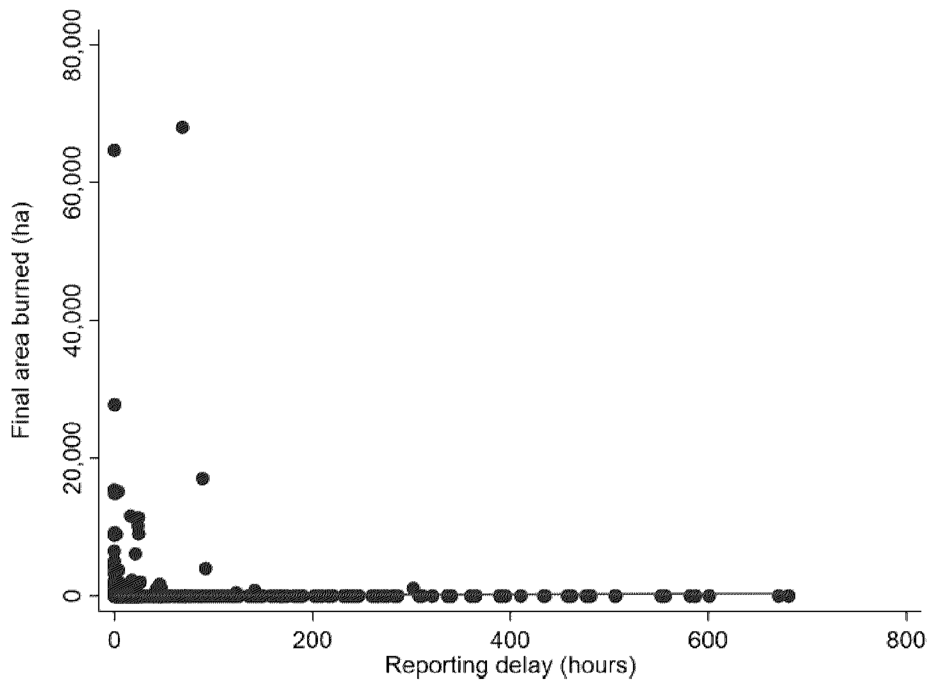

Fig 5. Scatter plot of final area burned and reporting delay.

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(>200 ha) represent only 2.1% of total fire counts (see Table 1), yet exceeded 88% of total fire suppression cost. Moreover, while the total cost for suppression of all 2019 fires was $282 million, half of this amount is accounted by one individual wildfire.

Second, fire size is an endogenous variable in empirical models of suppression expenditures. While fire size is an important predictor of suppression expenditures, suppression effort (and consequently its costs) will influence fire behavior and ultimately impact the final area burned. This constitutes reverse causality and generates biases in the estimates of all coefficients in the model. That is, if the objective is to estimate the impact of reporting delay on suppression costs, controlling for fire size will introduce bias.

While we fully expect the omission of fire size from the cost model to reduce its predictive power, such a strategy removes endogeneity bias due to reverse causality. However, failing to control for fire size would still generate bias if the final area burned is affected by wildfire reporting delays, i.e. omitted variable bias. While this is a theoretical possibility, we do not find support in the data for such a hypothesis.

We perform several analyses to investigate the nature of the relationship between fire size and reporting delay. Fig 5 shows the scatter plot of the final area burned and reporting delays (remark: to improve presentation, the figure omits three fires with final area burned greater than 200 thousand hectares). While the figure shows a wide range of reporting delays, we find no evidence that fire size increases with their reporting delays. This informal visual inspection suggests that the two variables are uncorrelated. A formal test is obtained by estimating a liner regression of fire size on reporting delay. We cannot reject the null hypothesis of no statistical relationship between the two variables (the slope coefficient is equal to 0.377, with p-value 0.402).

The analysis above examines the intensive margin of the relationship between fire size and reporting delay. We further investigate possible correlations between the two variables by

Table 3. Summary statistics, by fire size class.

	N	Mean	Std Dev	Min	Max
Size class A (<0.1ha)					
Cost (2020 Canadian dollars)	2965	4,945.45	7,760.77	6.78	127,382.41
Log cost	2965	7.24	1.92	1.91	11.75
Reporting delay (hr)	2965	12.61	51.87	0.00	681.36
Temperature (C)	2965	20.75	5.51	-9.10	33.00
Wind speed (km/h)	2965	16.79	6.22	3.50	50.00
Rain (mm)	2965	1.48	3.26	0.00	40.27
Relative Humidity (%)	2965	36.42	10.72	10.00	89.00
Fuel type: Timber slash	2965	0.56	0.50	0.00	1.00
Fire type: Crown fire	2965	0.02	0.13	0.00	1.00
South Aspect (true south)	2965	0.20	0.40	0.00	1.00
High elevation	2965	0.12	0.33	0.00	1.00
Lake/River within 3km	2965	0.33	0.47	0.00	1.00
Size class B (0.1 to 4ha)					
Cost (2020 Canadian dollars)	1645	22,667.05	33,033.79	26.32	311,946.00
Log cost	1645	8.94	1.80	3.27	12.65
Reporting delay (hr)	1645	10.01	38.53	0.00	478.74
Temperature (C)	1645	20.88	5.72	-2.50	33.40
Wind speed (km/h)	1645	17.33	6.43	0.00	47.00
Rain (mm)	1645	1.05	2.50	0.00	27.93
Relative Humidity (%)	1645	34.91	10.21	11.00	100.00
Fuel type: Timber slash	1645	0.61	0.49	0.00	1.00
Fire type: Crown fire	1645	0.06	0.23	0.00	1.00
South Aspect (true south)	1645	0.21	0.41	0.00	1.00
High elevation	1645	0.05	0.22	0.00	1.00
Lake/River within 3km	1645	0.31	0.46	0.00	1.00
Size class C (4 to 40 ha)					
Cost (2020 Canadian dollars)	324	148,458.20	174,134.82	21.89	976,246.13
Log cost	324	11.02	1.75	3.09	13.79
Reporting delay (hr)	324	10.49	35.75	0.00	336.31
Temperature (C)	324	22.27	5.84	0.70	31.70
Wind speed (km/h)	324	17.70	6.58	5.00	43.00
Rain (mm)	324	1.05	2.76	0.00	25.23
Relative Humidity (%)	324	33.97	9.62	12.31	59.67
Fuel type: Timber slash	324	0.72	0.45	0.00	1.00
Fire type: Crown fire	324	0.21	0.41	0.00	1.00
South Aspect (true south)	324	0.23	0.42	0.00	1.00
High elevation	324	0.07	0.25	0.00	1.00
Lake/River within 3km	324	0.19	0.39	0.00	1.00

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examining the extensive margin. Specifically, we investigate the possibility that reporting delays play a role in determining fire size classifications. Because size class is a discrete and ordered variable, we use ordered probit models to test whether reporting delay influences the probability that a fire evolves to a higher size class. We estimate models with and without controls (weather, fuel type, topography–see Table 3). In both cases, we cannot reject the null hypothesis of no influence of reporting delay on fire size class (p-values are 0.179 and 0.240 for models with and without controls, respectively).

Collectively, the results above suggest that reporting delay is not a significant determinant of fire size. This finding is largely in line with recent findings regarding the determinants of wildfire size in Alberta. Tymstra et al. (2021) analyze 80 large spring wildfires (>1,000 ha) across three decades and attribute dry, windy weather patterns as strong drivers of fire spread [37]. Using a sample of lightning-caused fires in Alberta, Tremblay et al (2018) apply survival analysis to quantify the effects of weather, fuels, and fire suppression activities on fire size [38]. They find that weather conditions such as low fuel moisture and high wind speeds are strongly associated with fire size. More recently (2023), Alberta faced an unprecedented fire season in which 36 fires over 10,000 ha contributed to a total of 2.2 million hectares area [39]. Beverly and Schroeder (2024) recognize that fire prevention and detection could be improved, however, they contend that the vast scale and range of fires in 2023 meant that suppression resources had to be triaged. Strategies to prioritize the protection of communities and other high-value assets led to a scenario in which many fires, which would have otherwise been addressed, were allowed to grow in size [39].

A final evidence regarding the fact that reporting delay is orthogonal to fire size class comes from testing for mean differences between reporting delays of fires from the different size class. We perform pairwise tests of the following null hypothesis: mean delay of class *i* minus mean delay of class *ii* equals to zero, where *i* and *ii* represent different size classes. None of the differences in means are statistically significant at the 5% level. This is evidence that fires that grow and eventually produce a large burned area are not detected with different times (on average).

In summary, the arguments above suggest that unspecified fire size is orthogonal to reporting delay in our suppression cost model. As such, we omit fire size to avoid reverse causality bias. Moreover, because Alberta Wildfire protocol specifies minimum levels of suppression resources for each fire class, we estimate the impact of reporting delays on costs by fire class. While Alberta Wildfire recorded over 7,500 fires from 2015 to 2020, we focus on fires of class A (<0.1 ha), B (0.1–4 ha) and C (4–40 ha), because, compared to size D and E fires, both the multitude of observations and the relative uniformity of expenditures make the subset of fires in class A-C more conducive to analysis by ML models.

Following previous wildfire expenditure research [40–44], log transformation is used both to make the cost distribution more symmetric and to address challenges related to heteroscedasticity. As well, the log-linear specification allows us to interpret the effect of reporting delay as a percentage of the suppression expenditure. Fig 6 shows the distribution of the logarithm

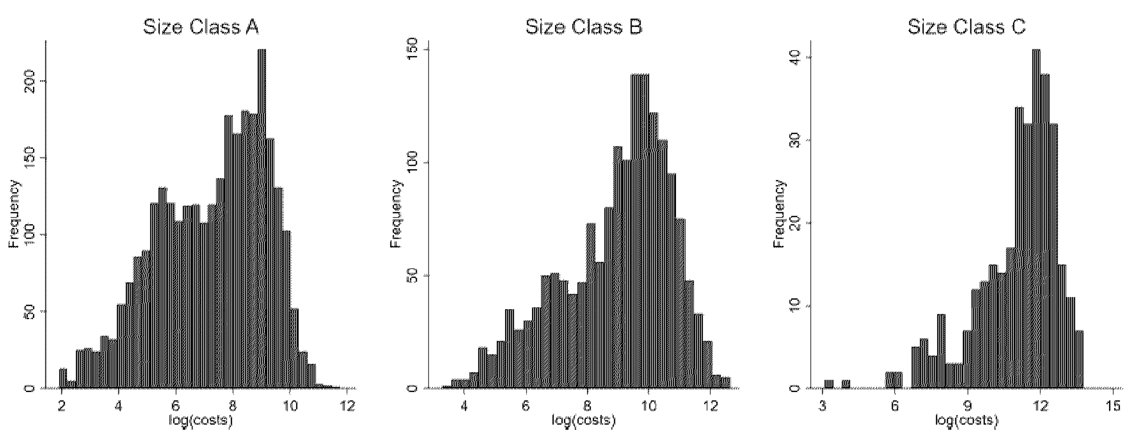

Fig 6. The distribution of log(costs), by size class.

https://doi.org/10.1371/journal.pone.0313200.g006 of suppression costs, by fire size.

Finally, wildfires respond in complex and nonlinear ways to variation in the fire environment. We have no information on the shape of the influence of weather, fuel type, and the topography of the land area on suppression expenditures. As we discuss below, instead of making arbitrary parametric assumptions, our approach involves using Random Forests to non-parametric recover this relationship from the data.

3.2 Fire environment

Alberta Wildfire also provided a dataset with daily weather observations for 499 weather stations throughout the Forest Protection Area, across the timeframe of our study period. While some papers use a fire weather index to control for weather conditions [40, 43, 45], we follow Bayham and Yoder and calculate individual weather variables from raw information in the Alberta Wildfire weather dataset [46]. The weather variables are created using observations of every weather station within 50 km from the coordinates of the fire ignition point. Establishing a distance threshold is important because the range and accuracy of wildfire weather stations is highly dependent on local conditions, and after consulting Alberta Wildfire we were unable to determine range precision for stations in our dataset. At the 50 km buffer, stations cover 7,522 of 7,525 ignition points in our dataset. For a deeper discussion, the reader should refer to papers in the fire weather literature [47–49].

We recognize there is the possibility of two-way causal relationship between fire weather and suppression costs, particularly in large, long-lasting fires. In such scenarios, it is possible that weather conditions drive fire behaviour, which in turn affects suppression costs, while simultaneously, costs reflect suppression efforts that will alter fire growth and behaviour, which in turn can impact regional weather conditions. To mitigate endogeneity, we focus on weather observations that drive a fire in its initial period, which we define as five days centered on the assessment date. In summary, we calculate maximum temperature, maximum wind speed, total precipitation and minimum relative humidity.

We control for the influence of topography on fire behavior using calculated aspect and elevation variables [40]. These variables are sourced from Altalis, a public-private provider of geospatial data. Using the 100-metre raster projection of the Alberta Provincial Digital Elevation Model, we create a dummy variable equal to 1 for fires whose origins are on the south aspect of a slope (between 135–225˚, where the landscape receives the most sun exposure), zero otherwise. We also create a dummy indicator for fires located in high elevation (over 1250 m, which is approximately the elevation of the start of the eastern slopes of the Rocky Mountains).

3.3 Summary statistics

As we focus on the impact of reporting delay on fires that received suppression expenditure, we exclude fires that had zero dollars for suppression (n = 839). Additional observations have been excluded when values were missing in their data source, such as fires for which there were no reliable weather data, as Alberta Wildfire stations were too far away (n = 274), and those for which fuel type were not recorded by Alberta Wildfire (n = 895).

Table 3 reports summary statistics for the fire-level variables, by fire size class. As expected, the average suppression costs increase with fire size. For class A fires, average cost is $4,945 (Canadian dollars of 2020). This value increases to $22,667 for class B, and to $148,458 for class C fires. The most expensive fire in our sample amounted to almost one million dollars in suppression costs. Average reporting delay hovers between 10–12 hours. A small proportion of fires are reported with no delay, i.e. 145 size A fires, 46 size B, and 10 size C. Both suppression costs and reporting delays have significant variance and their coefficient of variation is above 1 in all cases. The goal of the paper is to exploit this high variability to associate variation in suppression costs with variation in reporting delays, within fire size class, and holding constant fire environment, e.g. weather and landscape.

Regarding weather variables, average maximum temperature at fire ignition is about 21 degrees Celsius for fires type A and B, but about 1.5 degrees higher for fires that grow to class C. Wind speed, precipitation, and relative humidity are, on average, similar between size classes. Larger fires have more challenging fuel and fire type profile. Fifty six percent of fires in class A are fires that have timber slash as their primary fuel type. This statistic increases to 61% for class B and 72% for class C. Similarly, crown fires make up only 2% of class A fires, but 6% of class B fires and 21% of class C fires. Finally, regarding terrain topology, about 20% of fires start in locations with south aspect, and between 5–12% start in areas with high elevation. The presence of a water body near the location of a fire can be a significant factor in explaining suppression costs. While about 31–33% of fires size class A and B have a lake or river nearby, for size class C, only 19% of fires are within 3 km from bodies of water.

The next section discusses the machine learning method we use to estimate the impact of fire detection delays on fire expenditures.

4. Methods

The goal of the paper is to estimate the impact of reporting delays on suppression costs, holding the fire environment constant. We are interested in the following system,

$$Y_{it} = \beta D_{it} + g(X_{it}, \delta_t) + \varepsilon_{it} \tag{1}$$

$$D_{it} = m(X_{it}, \delta_t) + \mu_{it}, \tag{2}$$

where Eq (1) is the outcome equation and Eq (2) models wildfire detection. Specifically, Y_{it} represent (log of) suppression cost of fire i in season t,D is reporting delay, X are confounding variables that describe the fire environment, δ captures season effects, ε and μ are zero-mean error terms. The function $g(.)$ captures the influence of the fire environment and fire season on suppression costs. Importantly, Eq (2) allows for the fire environment and the fire season to influence reporting delays via the function $m(.)$.

While the system above is conceptually flexible, it creates empirical challenges due to the nature of the relationships between fire environment, suppression costs, and reporting delays, i.e. the nuisance parameters $g(.)$ and $m(.)$ may represent complex and highly nonlinear relationships. For example, the econometrician does not know the true functional form of the influence of temperature, wind speed, elevation, etc. on the suppression outcome, nor how these variables may influence reporting delays. While our focus is on the impact of reporting delays on costs, which is measure by β, misspecification of nuisance parameters can bias the relevant policy estimates.

To avoid parametric misspecification bias, empirical approaches should rely on nonparametric estimation of $g(.)$ and $m(.)$. Kernel regressions are a classic nonparametric method to perform such an estimation. However, slow convergence rates due to the curse of dimensionality make these nonparametric regressions less appealing in small sample applications such as ours [50]. Machine Learning (ML) offers state-of-the-art nonparametric approaches to fit the functions $g(.)$ and $m(.)$ to the data. In this paper, we use Random Forests to fit the functions $g(.)$ and $m(.)$ [51].

Tree-based models are among the most applied ML techniques [52]. Random Forests employ multiple decision-trees on many sub-samples of the data, with random subsets of the features for node splits. In regression problems, the method uses averaging to improve predictive accuracy [51]. As Random Forests ensemble multiple decision trees, they tend to reduce overfitting and more adequately fit nonlinear relationships [53]. Random Forests have been instrumental in empirical work in a wide array of wildfire applications. A review of the ML literature found that Random Forests are the most used algorithm in wildfire science [54]. For example, many papers have used Random Forests to perform fuel classification [55–57] and lightning prediction [58]. Random Forest models have also been shown to have superior performance in burned area assessment [59].

However, the direct application of a ML algorithm in the context of our system is challenging. The issue is related to the estimation of a one-dimensional causal parameter β in a model where high-dimensionality parameters such as $g(.)$ and $m(.)$ are unknown and must also be uncovered from the data using ML. Chernozhukov and co-authors show that regular ML can be applied to the system above and successfully predict Y and D, however, the estimate of the one-dimensional parameter is severely biased [28]. This happens because ML implements regularized estimators in order to optimize prediction and off-the-shelf algorithms are not designed to obtain a causal (unbiased or consistent) estimate of a single parameter. In our application, this parameter is the main parameter of interest, β: the impact of reporting delay on suppression costs.

Chernozhukov et al. propose the implementation of Double Machine Learning (DML) to de-bias the estimate of β. Based on a Frisch-Waugh-Lovell approach, the DML addresses regularization bias using orthogonalization. The procedure involves three steps: i. use Random Forests to predict Y from X and δ (fire season dummies); ii. similarly, obtain Random Forests predictions of D from X and δ, and finally; iii. perform a residual-on-residual regression to obtain a bias-free estimate of β. The DML also involves sample splitting and cross fitting to reduce overfitting bias and addresses issues of loss of statistical power. In this paper, we adopt the following orthogonalization algorithm to estimate β.

I. Randomly split the sample into two subsamples, namely A and B.

II. Using subsample A:

   i. compute the Random Forest prediction $\hat{Y}^A$ from X^A and δ^A

   ii. compute the Random Forest prediction $\hat{D}^A$ from X^A and δ^A

III. Using observations Y and D from subsample B:

   i. compute residuals $y^A_B = Y^B \quad \hat{Y}^A$

   ii. compute residuals $d^A_B = D^B \quad \hat{D}^A$

IV. Estimate $\hat{\beta}^A_B$ *a la* Frisch-Waugh-Lovell by linear regression of y^A_B on d^A_B, where $\hat{\beta}^A_B$ is the slope coefficient

V. Repeat steps II-IV by reverting the sample roles to compute $\hat{\beta}^B_A$

VI. Compute $\hat{\beta}_j = (\hat{\beta}^A_B + \hat{\beta}^B_A)/2$

VII. Repeat steps I-VI J times (we use $J = 400$)

VIII. Finally, compute $\hat{\beta} = \sum_j \frac{\hat{\beta}_j}{J}$.

The Random Forest predictions in step II are obtained using the R package Generalized Random Forests–GRF [60]. The package uses cross-validation to tune the following training parameters:

- Tree-growing parameters:
  - the fraction of the data used to grow trees (the number of trees is set to 2000)
  - the number of variables in each split
  - the minimum number of observations in each leaf
- Honest splitting [61]:
  - whether to implement sub-sample splitting, also known as 'honest forests', i.e. an additional split into halves of the fractional subsample, one for tree splitting (constructing the trees) and one for populating the leaf nodes (making predictions)
  - The fraction of the honest split used to select tree splits is also tuned within the range [0.5–0.8]
  - whether or not to prune away empty leaves after training
- Split balance parameters:
  - the maximum imbalance of a split (α), i.e. the size of a child node must be at least α^*size (parent)
  - an imbalance penalty (δ) to discourage child nodes from having very different sizes; δ * (1/ size(left.child) + 1/ size(right.child))

The cross-validation procedure uses one hundred random draws in the parameter space, trains forest for each set of parameters, and computes out-of-bag errors. Next, a smoothing function of errors is estimated and the values that minimize smoothed errors are chosen as the parameters of the tuned model (refer to https://grf-labs.github.io/grf/REFERENCE.html for additional details on parameter tuning).

The approach above produces an empirical distribution of the DML parameter β that can be used for statistical inference and hypothesis testing. To control for size effects and unobserved heterogeneity in environmental and policy factors due to size class, we apply our algorithm separately across subsets of size class A, B, and C.

5. Results

Fig 7 shows scatter plots of log costs on reporting delay, by fire size class. Observations in which reporting delay exceeds 30 days have been excluded due to concerns with transcription errors in the dataset as well as to eliminate outliers. The figure shows the linear prediction of costs from reporting delays. This preliminary analysis reveals a positive correlation between the two variables, i.e. larger reporting delays are associated with larger suppression costs.

Table 4 reports the estimates $\hat{\beta}$ of the impact of reporting delay on the log of suppression cost, by fire size class. The results indicate that one additional hour of reporting delay increases suppression costs by 0.256% for fires of size class A ($p<0.01$), 0.246% for size class B ($p<0.01$), and 0.280% for size class C ($p<0.01$).

While the coefficients are similar in magnitude across size classes, their economic significance varies. For example, given that the average expenditure incurred in the suppression of a size class A fire is $4,945.45, an additional hour of delay increases total suppression cost by

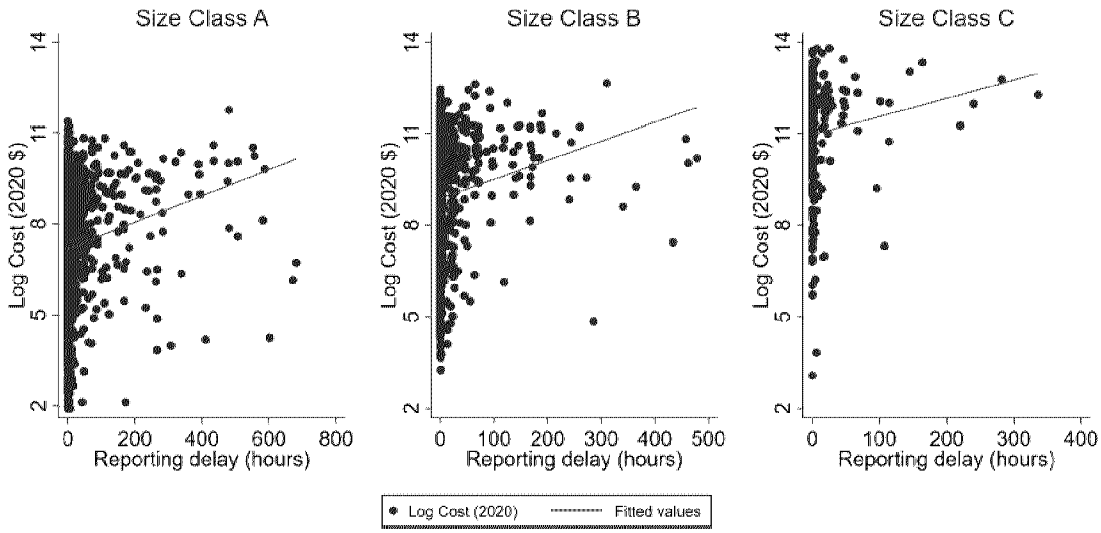

Fig 7. Log cost and reporting delay, by fire size class.

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$12.66. For size class B, the average cost is $22,667.05, so the additional cost of an hour of delay is $55.76. Finally, for size class C with average cost of $148,458.20, the marginal cost increment is $415.68.

The numbers above can also be used to predict, on average, the contribution of wildfire detection to total suppression costs. Class A fires are detected with an average reporting delay of 12.61 hours. Using the marginal (or per hour) valuation estimate of $12.66, the contribution of reporting delays to suppression costs is, on average, only $159.64 per fire, which represents only 3.2% of the average suppression costs. Using the same method, the contribution of reporting delays to the costs of suppression of fires in size class B is, on average, $558.19 per fire, or 2.5% of average costs. Finally, for size class C, reporting delays cost $4,360.48 per fire (on average), which represents 2.9% of the average total suppression costs.

6. Discussion

While early detection is generally assumed to be a critical component in cost-effective wildfire suppression (refer to Duff et al. (2015) [62] for a review), empirical literature on the effect of early detection on suppression cost is limited [62–64]. In performing a cost-benefit analysis of lookout towers in Wisconsin, Steele and Stier find that while the cost of operating lookout

Table 4. Estimates of the impact of reporting delay on ln(suppression costs), by size class.

	A	B	C
$\hat{\beta}$	0.00257***	0.00244***	0.00270***
	(5.965648e-06)	(1.007552e-05)	(3.364487e-05)
N	2,965	1,645	324

Notes: Fire size classes: A: <0.1 ha; B: 0.1–4 ha; C: 4–40 ha. Standard errors in parentheses.

* p<0.10

** p<0.05

*** p<0.01.

towers exceed their value in the reduction of direct suppression cost, the benefit of towers are realized in the reduction of total wildfire costs, which also include property loss [64].

Since the work of Steele and Stier, only a few studies have incorporated reporting delay (measured in time units) into a suppresion expenditure empirical model [40–42]. This literature reports mixed results with the effect of detection delay on costs typically not significant. As a part of a PhD dissertation, Lankoande applies linear regressions to a dataset of consisting of over 307 thousand fires from 1970 to 2002 covering the continental United States [42]. Three models are created in which suppression costs, burn area and damage costs are modeled on detection delay time, along with environmental, weather and population density variables. Detection delay time is expressed in units of log and log of the squared delay variable. The results indicate the puzzling effect that an increase in detection delay significantly decreases both suppression costs and the burn area at an increasing rate, but increases damage costs at a decreasing rate.

Acknowledging the model specification in Lankoande, Gebert et al. apply a further detailed linear regression model to a highly multi-dimensional dataset of US Forest Service-suppressed wildfires from 1995 to 2004 [40]. The dataset includes 1,550 fires that had escaped initial containment, from 100 acres (40 ha) to over 300 acres (121 ha). The authors examine suppression expenditure per acre as the dependent variable, stating that fire managers were accustomed to considering cost as per-unit area measurement. After separating the dataset into West/East regions, Gebert et al. model the suppression cost per acre for each wildfire as a function of many variables including the fire environment, values at risk, resource availability and reporting delay. Delay is included in both in log and squared log form. The delay effect was not significant in West, however in the East, a longer delay period decreases suppression cost per area up to 22.6 hours, at which point delay increases cost per area.

More recently in 2022, MacMillan et al. apply both parametric and nonparametric methods for suppression expenditures of 5,459 fires in the Canadian province of British Columbia, which neighbours Alberta, from 1981 to 2014 [41]. The study uses a negative binomial regression to address the non-normal cost distribution, right-skewed by extremely expensive fires. Nonparametric ML models include Random Forests as well as gradient boosting. When both parametric and nonparametric models are used to forecast out-of-sample fires, the researchers find that the models have similar predictive performance. Results from both parametric and ML models indicate that the effect of log detection time delay is marginally significant ($p<0.10$) in slightly reducing expenditure. MacMillan et al propose that the negative effect of delay on cost may reflect the possibility that fires in remote areas receive lower fire management priority.

Our analysis of the detection-expenditure nexus excludes large wildfires. As discussed above, the relationship between suppression expenditures and wildfire size is largely nonlinear (see Fig 4). Typically, the development in size (and consequentially suppression expenditure) of large-scale wildfires are attributed to factors beyond the reporting delay during the initial phases of a response protocol. This observation is substantiated by the findings of an external review commissioned by Alberta Wildfire for the notable 2016 Horse River (Fort McMurray) Wildfire (size class E at over 600 thousand hectares). The review determined that fire development was due to a combination of environmental factors (low relative humidity, high temperatures, high wind speed and gusts), as well as concurrent fires in the region that also required suppression resources. Further, the report concludes that "time lag is not believed to be inordinately long as the wildfire was detected at a size of less than 2.0 hectares–within expectations set for the detection program" [65]. Given the potential for a myriad of new variables to arise with the size of a fire complex, especially for fires that significantly deviate from seasonal norms, in this study, we focus on an analytical sample of 4,934 fires ranging from size class A to class C. By narrowing our scope, we discover the specific impact of reporting delay on suppression costs, for fires that have been successfully suppressed before reaching a critical size.

7. Conclusion

The Double/Debiased Machine Learning (DML) approach delivers precise estimates of the policy parameter β. The results indicate that reducing the delay between ignition and reporting of a wildfire delivers statistically significant (albeit modest) effects in reducing suppression expenditures; $\hat{\beta} \approx 0.0026$ ($p<0.01$). Contrary to the previous studies that show reporting delay to have a negative effect on suppression costs [40–42], in our DML model we find that a reduction in reporting delay decreases fire suppression expenditure. Specifically, we find that each hour of reporting delay reduction tends to reduce the cost of suppression by approximately 0.25% ($p<0.01$).

These results give decision makers in Alberta Wildfire empirical evidence that investments in improving early detection has discernable payoffs in reducing total suppression cost. For instance, in our dataset, the average reporting delay of a size C fire in 2019 was 6.77 hours. If reporting delay was reduced by one hour for each of the 54 size C fire observations in this subset, total expenditure across all fires could have been reduced by $31,000. This reduction represents a modest proportion of suppression costs, as the average cost for suppressing a size class C fire in 2019 was $201,800.

Nonetheless, it is possible that the benefits of early detection and reporting are further realized when taking into account the reduction of total wildfire damage costs, which includes loss of property and assets [64]. Taking into account our empirical results on suppression expenditure savings, as well as the consideration of further possible reductions in wildfire damage costs, wildfire managers are better informed to consider how worthwhile it may be to upkeep existing detection systems (i.e. lookout towers and reporting lines), and the possible utility of adopting new tools like UAS and other automated technologies.

In recent years, new technologies like UAS and deep-learning are showing promising steps to reducing the impact of wildfires [66–68]. Whatever are the tools being utilized, our research suggests that initiatives to reduce reporting delays have statistically significant impacts (albeit modest in magnitude) on reducing the costs incurred in fire suppressions. As such, investments to improve the detection of wildfires and reduce reporting delays are more reasonably justified on the basis of socioeconomic gains beyond the savings that prompt detection generates on suppression costs.

7.1 Limitations

We recognize that economic modelling of suppression costs continues to have its limitations, despite the methodological improvements of new frameworks like DML. Wildfire suppression is a complex topic, and the interaction between environmental and human variables are challenging to model. For instance, effects such as media coverage or political influence have been proven to impact suppression costs [69], though such effects are not addressed in our models. In our study, we have excluded fires that are difficult to account, such as those formed as part of a larger “fire complex”. However, we must recognize that it is often extreme fire events that drive the bulk of wildfire expenditure, highlighting the need for further examination of fire complexes.

While the paper investigates the potential to influence suppression costs via early wildfire detection using a machine learning model that controls for nonlinear effects of the fire environment, our approach is not able to incorporate data of larger fires (class D and E). This is a significant limitation as those fires are responsible for a disproportionate share of suppression expenditures. Nevertheless, our findings suggest that suggests that reporting delay is not causing fires to grow to a higher fire class. Future work is need to address the challenges of working with large fire data, including the skewedness of the cost distribution and the fact that certain elements of the fire attack may be responsible for the bulk of expenses (e.g. aircrafts) thus reducing the variation available to estimate the impact of other observables.

The cost of operating air tankers, helicopters, and other aircraft make up a substantial portion of suppression expenditures of large wildfires; aircraft is critical both in directly tackling flames and in limiting the spread of fire via laying retardant barriers retardant [70, 71]. Future work is necessary to investigate viable alternatives to the deployment of aircraft [72], and to define the metrics for assessing the supply and demand of suppression resources [73].

Our approach to estimate impacts by fire size class, while beneficial for accommodating the skewedness of the data, suffers from limitations. Since we do not model what determines the size of each fire, our models are estimated in selective samples. As such, our estimates do not represent the impact of reporting delay on the cost of a random fire. Instead, the paper provides an impact estimate for each type of fire. While conceptually less general, in practice our approach is informative since we find similar results across the different types of fires, i.e. our impact estimates are equal to 0.0026, 0.0024, and 0.0027 for fires size class A, B, and C respectively. In other words, for the fires in our sample, an increase in detection delay of one hour leads to an increase in suppression costs of about 0.025%.

Finally, another limitation of the model is the linearity assumption of in Eq (1). While the outcome equation is flexible regarding the influence of fire environment on suppression costs, the model adopts a parsimonious approach regarding the influence of reporting delays on costs. While the simple linear parametrization makes β estimates easy to interpret, it is possible that, even after controlling for nonlinear effects of fire environment, the effects of reporting delays on costs can be nonlinear. Future work is needed to adapt the methods employed in this paper to accommodate this additional source of nonlinearity.

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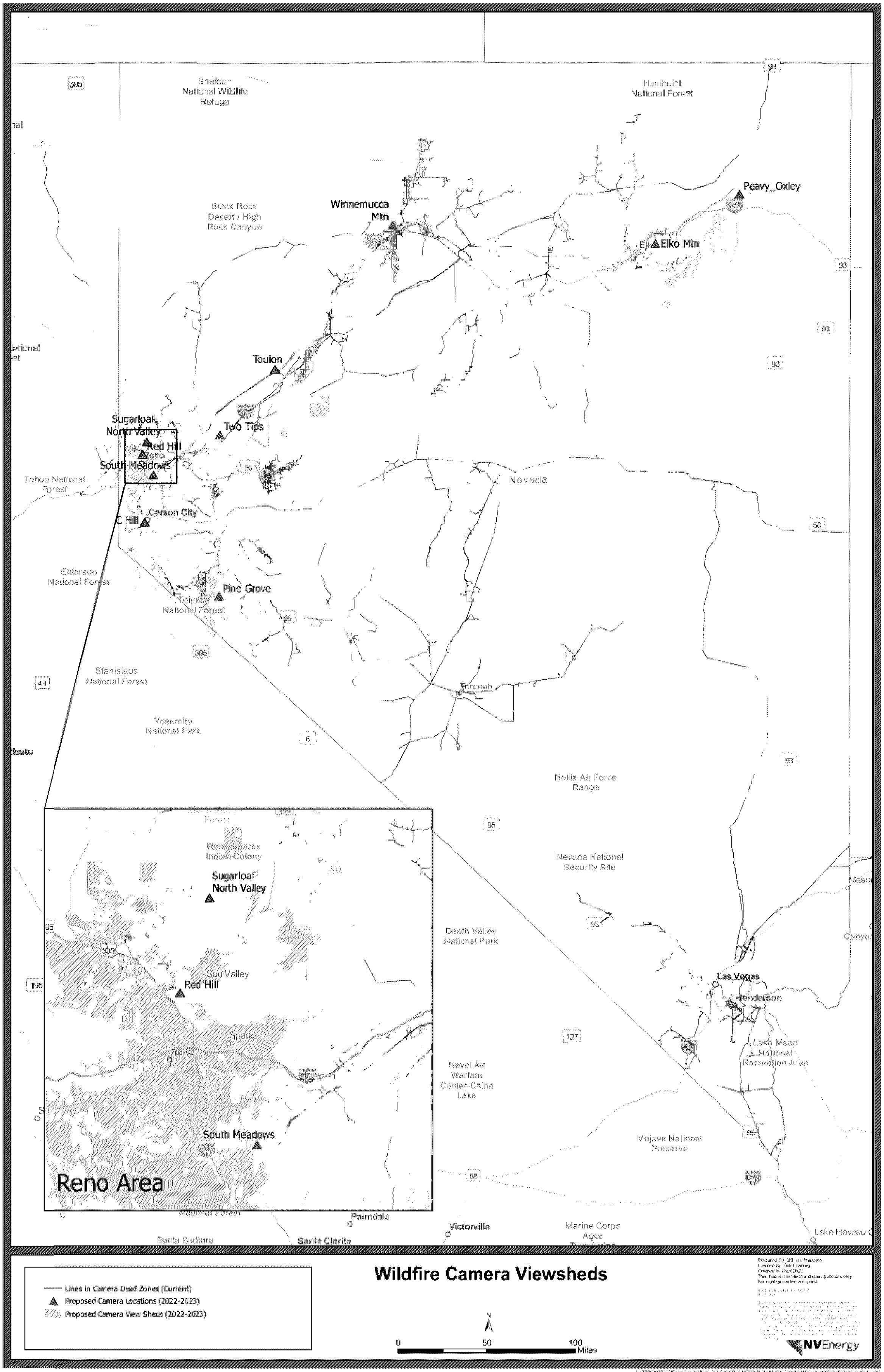
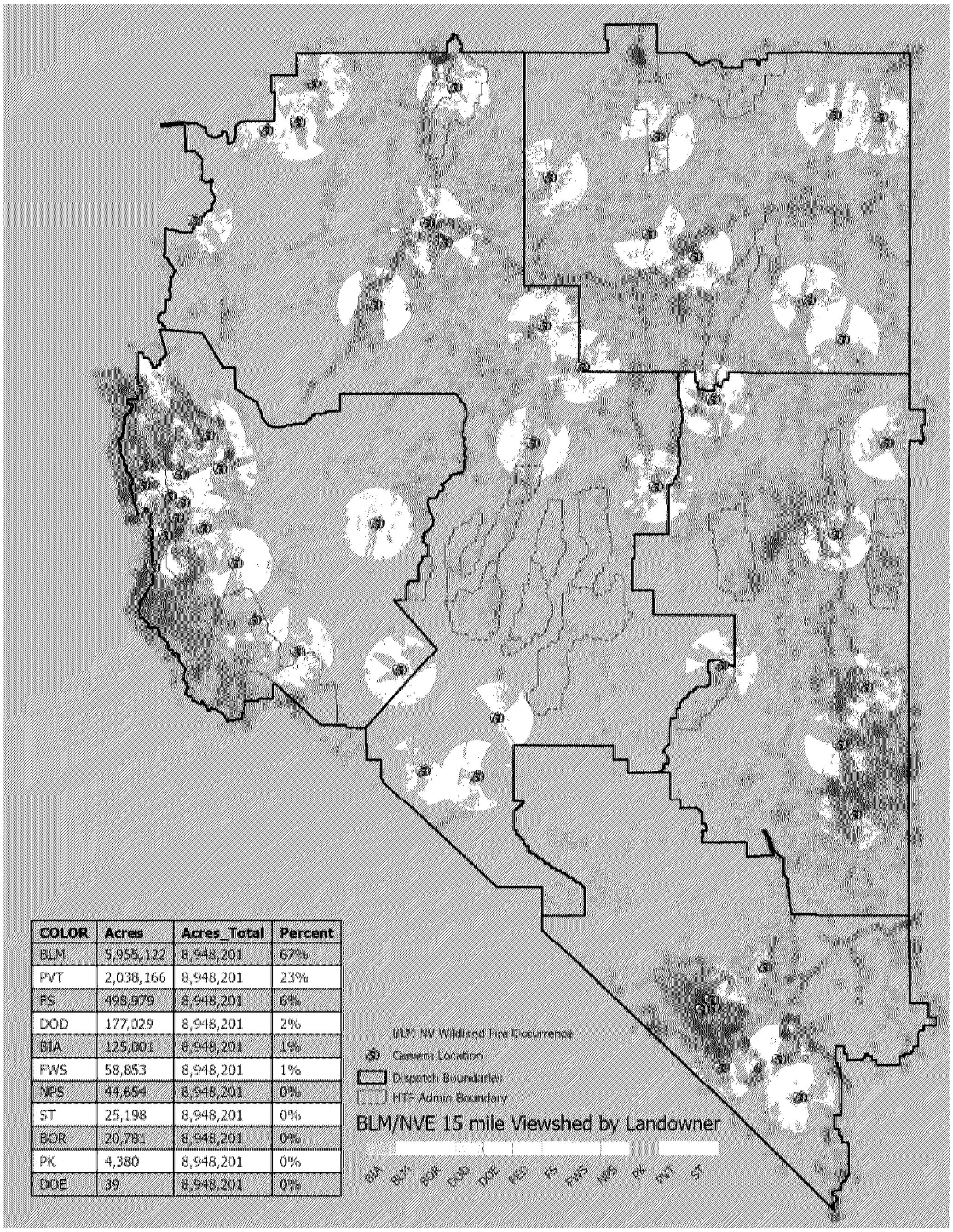

Wildfire Camera Viewsheds
Lines in Camera Dead Zones (Current)
Proposed Camera Locations (2022-2023)
Proposed Camera View Sheds (2022-2023)
Peavy_Oxley
Winnemucca Mtn
Elko Mtn
Toulon
Two Tips
Sugarloaf North Valley
Red Hill
South Meadows
C Hill
Carson City
Pine Grove
Reno Area
Sun Valley
Sparks
Reno
Nevada
Las Vegas
Henderson
Nellis Air Force Range
Nevada National Security Site
Death Valley National Park
Yosemite National Park
Stanislaus National Forest
Eldorado National Forest
Tahoe National Forest
Toiyabe National Forest
Black Rock Desert / High Rock Canyon
Humboldt National Forest
Sheldon National Wildlife Refuge
Lake Mead National Recreation Area
Mojave National Preserve
Naval Air Warfare Center-China Lake
Palmdale
Victorville
Santa Clarita
Santa Barbara
Marine Corps Agcc
Lake Havasu
0
50
100
Miles
NVEnergy



COLOR	Acres	Acres_Total	Percent
BLM	5,955,122	8,948,201	67%
PVT	2,038,166	8,948,201	23%
FS	498,979	8,948,201	6%
DOD	177,029	8,948,201	2%
BIA	125,001	8,948,201	1%
FWS	58,853	8,948,201	1%
NPS	44,654	8,948,201	0%
ST	25,198	8,948,201	0%
BOR	20,781	8,948,201	0%
PK	4,380	8,948,201	0%
DOE	39	8,948,201	0%

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RESEARCH ARTICLE

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An AI-Based Early Fire Detection System Utilizing HD Cameras and Real-Time Image Analysis

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Abstract: Wildfires pose a significant threat to human lives, property, and the environment. Rapid response during a fire's early stages is critical to minimizing damage and danger. Traditional wildfire detection methods often rely on reports from bystanders, leading to delays in response times and the possibility of fires growing out of control. In this paper, ask the question: "Can AI object detection improve wildfire detection and response times?". We present an innovative early fire detection system that leverages state-of-the-art hardware, artificial intelligence (AI)-powered object detection, and seamless integration with emergency services to significantly improve wildfire detection and response times. Our system employs high-definition panoramic cameras, solar-powered energy sources, and a sophisticated communication infrastructure to monitor vast landscapes in real time. The AI model at the core of the system analyzes images captured by the cameras every 60 s, identifying early smoke patterns indicative of fires and promptly notifying the fire department. We detail the system architecture, AI model framework, training process, and results obtained during testing and validation. The system demonstrates its effectiveness in detecting and reporting fires, reducing response times, and improving emergency services coordination. We have demonstrated that AI object detection can be an invaluable tool in the ongoing battle against wildfires, ultimately saving lives, property, and the environment.

Keywords: wildfire detection, artificial intelligence, object detection, panoramic cameras, solar-powered system

1. Introduction

Wildfires pose a significant threat to human lives, property, and the environment. The rapid response during a fire's early stages is critical in determining the level of damage and danger it can cause. Traditional wildfire detection methods often rely on reports from bystanders, leading to delays in response times and the possibility of fires growing out of control. On average, Australia experiences around 50,000–60,000 bushfires annually, with estimated damage varying significantly depending on the severity and location of the fires.

A recent example of the devastating impact of wildfires can be seen in the Margaret River bushfires in Western Australia in 2011. These fires ravaged the area, destroying more than 30 homes and forcing over 200 residents to flee to safety. Smoke from the inferno engulfed the region, creating hazardous conditions and complicating firefighting efforts. The annual cost of bushfire damages in Australia is around AUD 1.6 billion, but this figure can be much higher in years with particularly severe fires, such as the 2019–2020 Australian bushfire season, which resulted in damages estimated to exceed AUD 10 billion. Given the potentially disastrous consequences of wildfires, there is a pressing need for more advanced and efficient detection methods to enable a faster and more effective response.

Recent advancements in artificial intelligence (AI), specifically convolutional neural networks (CNNs) [1], have demonstrated their potential to revolutionize various industries, including fire detection and response. CNNs have achieved exceptional performance in object classification [2–5], object detection [6–9], and object segmentation [10–12, 12, 13] on established image datasets and have found applications in autonomous driving, robotics, and video surveillance. Among these tasks, object detection is particularly relevant for fire detection, as it involves identifying the location and category of objects within an image, such as smoke or flames.

In this paper, we present an innovative early fire detection system that utilizes state-of-the-art hardware, AI-powered object detection, and seamless integration with emergency services to significantly improve wildfire detection and response times.

Our system combines high-definition panoramic cameras, solar-powered energy sources, and a sophisticated communication infrastructure to monitor vast landscapes in real time. The AI model at the core of the system analyzes images captured by the cameras every 60 s, identifying early smoke patterns indicative of fires and promptly notifying the fire department (see Figure 1). This approach ensures rapid response and coordination, minimizing the potential damage caused by wildfires.

This paper is organized as follows: Section 2 details the system architecture, including the camera system, solar power system, communication infrastructure, and public interface. Section 3 outlines the AI model architecture, focusing on the object detection model, dataset creation, and training process. Section 4 presents the results obtained during the testing and validation of the system, demonstrating its efficacy in detecting and reporting fires,

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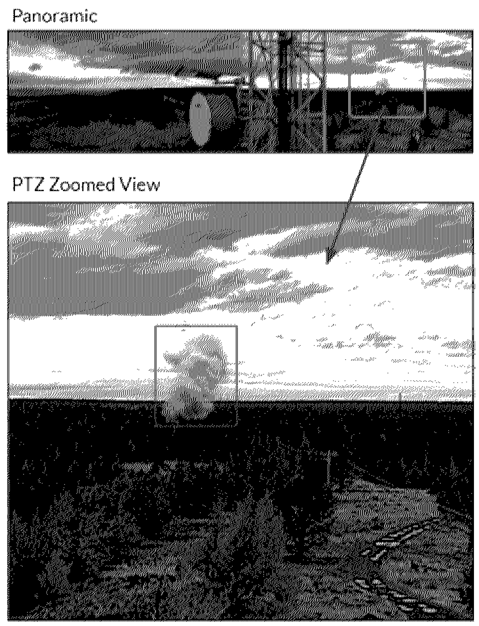
Figure 1
Detection of bushfire



reducing response times, and improving emergency services coordination. Finally, Section 5 discusses potential future work and enhancements to further improve the system's performance and capabilities.

In summary, this paper introduces a cutting-edge early fire detection system that combines high-definition cameras and AI-driven image analysis to revolutionize wildfire monitoring and response. By providing accurate, real-time information to emergency services, the system has the potential to significantly reduce the damage caused by wildfires and protect human life and property.

2. Review of Early Fire Detection Approaches

In recent years, the application of cameras for early fire detection has garnered significant attention, with several methodologies emerging as the most prevalent. The following literature review explores these methods and the research that underpins them:

Flame detection: One of the widely used techniques for fire detection involves the identification of unique flame features, such as flickering behavior, color, and shape. Celik [14] demonstrates that flame detection algorithms typically rely on image processing techniques to extract these features and recognize the presence of fire in captured images [14].

Smoke detection: Another common approach to fire detection is the analysis of images for specific smoke characteristics, including color, texture, and motion. Töreyin et al. [15] reveal that by detecting and tracking the movement of smoke, these algorithms can provide early warning of a developing fire [15].

Thermal imaging: Thermal cameras detect heat and create visual representations of temperature variations in the scene. By identifying temperature anomalies, this method can detect fires even in low visibility conditions, such as in the presence of smoke or fog [16].

Machine learning-based detection: With the advancements in machine learning and computer vision, various models have been proposed for fire detection using features learned by algorithms. Bouguettaya et al. [16] discuss the effectiveness of deep learning-based computer vision algorithms for early wildfire detection from unmanned aerial vehicles [16]. Akagic and Buza [17] present a lightweight wildfire image classification method using deep CNNs [17]. Wang et al. [18] explore forest fire image recognition based on CNNs [18].

For the current project, access to thermal imaging was unavailable, with only panoramic cameras at our disposal. However, we were not constrained to edge processing and had access to cloud computing power. Consequently, we opted to utilize the machine learning-based detection approach for our fire detection system.

This research paper introduces an AI model capable of real-time processing of panoramic images. Notably, we employ cutting-edge object detection techniques, which distinguish our methodology from previous studies, such as the work conducted by Bouguettaya et al. [16], which utilizes image tessellation and object classification. Our approach, centered around object detection, demonstrates higher efficiency due to its independence from the need for image tessellation.

3. Research Methodology

The proposed early fire detection system consists of a sophisticated hardware setup and a communication infrastructure that seamlessly integrates with the AI model and fire department resources. This section outlines the key components of the system's architecture and their roles in ensuring effective and efficient fire detection and response.

3.1. Camera system

The entire hardware solution comprises three cameras and a solar power unit, mounted on a pole (see Figure 2). Two high-definition 180-degree cameras work together to create a comprehensive 360-degree panoramic view of the monitored landscape. A single high-definition pan–tilt–zoom (PTZ) camera is employed for detailed fire imaging and investigation. This PTZ camera can be remotely controlled from the control tower or by the AI system, allowing for adjustments in pan (x-axis), tilt (y-axis), and zoom as needed. The integration of a feedback loop between the software and the PTZ camera ensures optimal imaging and analysis.

3.2. Solar power system

The system utilizes state-of-the-art solar panels, a solar controller, and solar batteries with smart charging capabilities to ensure continuous operation in any environment (see Figure 2). The solar power system eliminates the need for external power supplies, making it suitable for remote deployment. The batteries have a life expectancy of 5 years, reducing the need for frequent maintenance and replacement.

3.3. Communication infrastructure

A reliable 4G connection is incorporated into the system, enabling 24/7 real-time internet connectivity for live streaming of images from the cameras to a cloud server. This high-speed connection also facilitates real-time feedback to the PTZ controller, ensuring efficient communication between the hardware components and the AI system. High-speed video links

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Figure 2
Camera and solar panel hardware

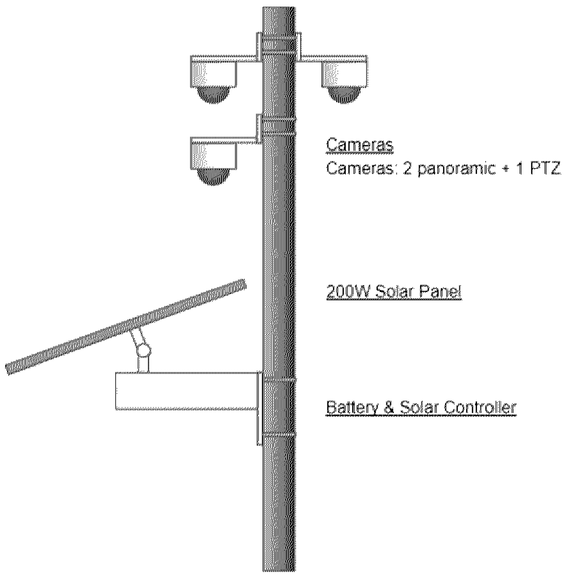
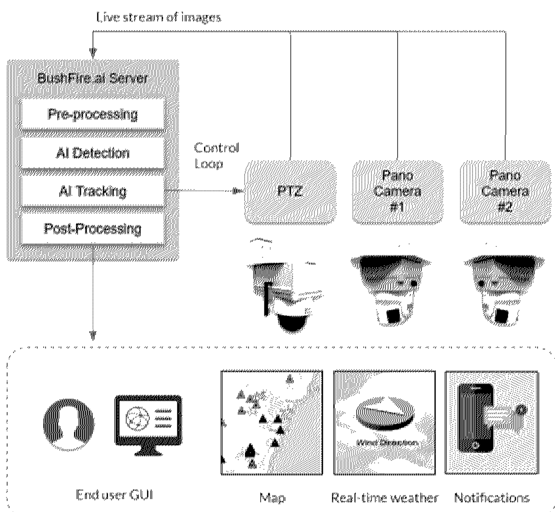


Figure 3
System architecture



provide seamless transmission of images to the AI system and the fire department for rapid analysis and response (see Figure 3).

3.4. Public access and interface

The software for the fire detection system is accessible to the public through the website bushfire.ai. This platform allows users to view real-time images from the camera system and receive information on detected fires, fostering awareness and community engagement in wildfire monitoring and prevention.

In summary, the system architecture consists of an advanced camera system, a solar power system, a communication infrastructure, and a user-friendly public interface. These components work together to create a robust and reliable early fire detection system that can be deployed in various environments, providing real-time data and images for effective fire detection and response.

4. AI Model Architecture

The AI component of the early fire detection system plays a crucial role in analyzing images captured by the camera system and identifying smoke patterns indicative of fires. This section describes the architecture of the AI model, including the methodology, object detection model, dataset creation, and training process.

4.1. Methodology

In this paper, we present a methodology for the development of an AI component for early bushfire detection. The AI model is designed to analyze 360-degree panoramic images, identify distinctive smoke trails and signs of fire, utilize object detection to recognize smoke or fire, track the movement of smoke over time, and map the direction of movement with known wind direction to correlate the direction of growth.

To process the images, the AI system employs a camera system that captures 360-degree panoramic images at a rate of one image per minute. These high-resolution images provide comprehensive coverage of the monitored area, enabling the early detection of emerging fires. The primary objective of the AI model is to identify distinctive smoke trails and signs of fire within the captured images, which is achieved by analyzing the visual features of the images, such as color, texture, and shape, to pinpoint potential fire-related patterns.

The AI model leverages advanced object detection techniques to accurately identify smoke or fire within the images. This involves training the model on a comprehensive dataset containing annotated images of smoke and fire, allowing it to learn the unique characteristics of these phenomena and distinguish them from other objects in the scene. In order to determine the direction of movement, rate of growth, and size of a detected fire, the AI model tracks the movement of smoke over time. By comparing consecutive images, the system can analyze the changing patterns of smoke and infer valuable information about the progression of the fire.

Lastly, the AI model maps the direction of smoke movement with known wind direction data to correlate the direction of growth of the fire. This information can be used to predict the likely path of the fire, facilitating more efficient and effective firefighting efforts. By integrating these methodologies, the AI-based early fire detection system can rapidly and accurately detect emerging bushfires, ultimately assisting in the timely mitigation of potential damages and loss of life.

4.2. Object detection model

The system incorporates a multitude of intricate steps, including pre-processing, various AI detection and classification models, and post-processing. This discussion provides a glimpse into one specific object detection model utilized within the pipeline. However, other components of the system are proprietary and cannot be disclosed.

Among the AI object detection models employed in this system, one is founded on the YOLOv5 architecture, an advanced deep learning model recognized for its exceptional accuracy and efficiency in identifying objects within images [6, 19–21]. Utilizing the PyTorch framework, the YOLOv5 model is configured to process input images with dimensions of 640 × 640 pixels, ensuring high-resolution analysis for precise fire detection.

4.3. Dataset creation

To train the AI model, a dataset of 20,000 images was created using panoramic cameras deployed across the United States and Australia. The images were collected over a 12-month period to account for variations in seasons and weather conditions, ensuring a diverse and representative dataset. The dataset was split into a 70% training set and a 30% validation set to evaluate the model's performance during the training process.

The dataset includes images with and without fire, and the model is trained to recognize both scenarios. Images were annotated by wildfire experts. Images without annotations, i.e., those without visible fires, are not ignored during training. This approach informs the model about the absence of fires, enhancing its ability to differentiate between fire and non-fire conditions.

4.4. Data augmentation

To improve the model's robustness and generalization capabilities, data augmentation techniques were applied during the training process. These techniques include horizontal flipping, scaling, brightness adjustments, hue changes, and saturation modifications. Vertical flipping was excluded from the augmentation process, as it may introduce unrealistic scenarios for wildfire detection.

4.5. Model training

The AI model was trained for 679 epochs, achieving a mean average precision (mAP) score (IoU@0.05:0.95) of 0.04 and an accuracy of 93.5% (see Table 1). The training process was halted at 679 epochs because the model's loss did not improve further, and additional training epochs led to overfitting and reduced generalization.

During the training process, the AI model learned to detect early smoke patterns from fires by analyzing the input images. It also learned to control the PTZ camera through the feedback loop, adjusting the camera's pan, tilt, and zoom settings to better capture and analyze fires.

In summary, the AI model architecture combines a powerful object detection model with a diverse dataset, data augmentation techniques, and an optimized training process. This comprehensive approach enables the early fire detection system to effectively identify and track the movement of smoke over time, enhancing the overall performance and utility of the system in wildfire monitoring and response.

4.6. Possible shortcomings

Within the domain of camera systems, the orientation of the cameras, in conjunction with the application of Zoom functionality and the presence of image distortion, holds the potential to exert an influence on the outcomes of AI detection. To ensure the adaptability and reusability of trained AI models, it is imperative to undertake the process of normalizing and deskewing raw images prior to their submission for AI inference. By implementing these measures, the effectiveness of AI detection can be enhanced, allowing for the preservation and continued utilization of trained AI models.

5. Results

The performance of the early fire detection system's AI model was evaluated based on its ability to accurately identify and report fires in their early stages. This section presents the key results obtained during the testing and validation process, demonstrating the system's efficacy and its potential to enhance fire response efforts.

The AI model achieved a mAP score (IoU@0.05:0.95) of 0.04 and an accuracy of 93.5% during the training process. These results indicate that the model is highly effective at detecting smoke patterns indicative of fires within the input images (see Figure 4). The trained AI model was able to identify early-stage fires with high precision, ensuring prompt notification of the fire department and facilitating rapid response efforts.

In addition to the detection performance, several anecdotal benefits have emerged from the implementation of the system:

Reduced response time: Anecdotal evidence suggests that the proposed system, which continuously monitors large areas with high-resolution cameras and employs the AI model for real-time image analysis, has significantly reduced response times compared to traditional fire reporting methods. This improvement in response time has the potential to greatly reduce the scale of wildfires and the associated damage to human life and property.

Web portal for first responders: The early fire detection system features a real-time dashboard tailored for first responders, integrating AI processing and facilitating communication and coordination among emergency services. This web portal not only

Table 1
Fine tuning parameters

Parameter	Value
Framework	PyTorch
Model	Similar to YOLOv5
Input size	640 × 640 pixels
Dataset size	20,000 images
Data augmentations	Horizontal flip, scale, brightness, hue, saturation
Number of epochs	679
Accuracy	93.5%
Loss	Not improved after 679 epochs
mAP score	0.041 (IoU@0.05:0.95)
Train/Val split	70% / 30%

Figure 4
Example detection of a fire

notifies the relevant fire department upon detecting a potential fire but also provides high-resolution images of the fire location, satellite map data with a weather overlay, and real-time information about fire department aircraft, which enhances situational awareness and decision-making.

Public engagement and awareness: The system promotes community engagement and awareness in wildfire monitoring and prevention by making the software accessible to the public through the https://bushfire.ai website. This platform allows users to view real-time images from the camera system and receive information on detected fires, fostering a sense of ownership and responsibility among community members.

These anecdotal benefits underscore the overall value of the early fire detection system in not only detecting and reporting fires but also improving response times, coordination of emergency services, and public engagement. The system's performance highlights its potential to significantly mitigate the impact of wildfires on human life, property, and the environment.

6. Future Work

While the current implementation of the early fire detection system has shown promising results, there are several areas for future research and development to further enhance its capabilities, effectiveness, and robustness. In this section, we discuss potential future work that could lead to improvements in fire detection, response times, and overall system performance.

The AI model could be improved by exploring other state-of-the-art object detection algorithms, such as Faster R-CNN, Single Shot MultiBox Detector (SSD), or EfficientDet. Additionally, incorporating transfer learning from pre-trained models on large-scale image datasets like ImageNet could potentially boost performance and reduce training time. Moreover, employing techniques such as model assembling or employing a multi-stage detection pipeline could help increase the overall accuracy and reduce false positives.

To further improve the AI model's generalization and robustness, the training dataset could be expanded to include images from diverse geographical regions, climates, and vegetation types. This would allow the model to better adapt to varying environmental conditions and fire behavior patterns. Furthermore, incorporating synthetic data generated through computer graphics or data augmentation techniques could help increase the dataset's size and diversity.

Integrating multispectral or hyper spectral imaging into the camera system could provide additional information about fires, such as temperature, chemical composition, and combustion stages. This additional data could be used to improve fire detection accuracy and provide more detailed information to emergency services, enabling them to better assess the situation and allocate resources accordingly.

Incorporating real-time weather data into the system's decision-making process could help improve the accuracy of fire detection and prediction. Factors such as wind speed, humidity, and temperature can significantly influence fire behavior and spread. By considering these factors, the system could potentially anticipate fire growth patterns and provide more accurate alerts and recommendations to emergency services.

Developing a fire spread prediction model based on factors such as terrain, vegetation, and weather conditions could help emergency services better anticipate the evolution of a fire and plan their response accordingly. By providing an estimation of the fire's future behavior, this prediction model could enable more effective resource allocation and response strategies.

To ensure reliable and real-time communication between the system, emergency services, and the public, the communication infrastructure could be further improved. This might include the implementation of a dedicated communication network for emergency services, the use of edge computing to reduce latency and improve data processing, or the development of a decentralized communication protocol to enhance system resilience.

In conclusion, there are numerous opportunities for future work to improve the early fire detection system's performance and capabilities. By addressing these areas, the system could become an invaluable tool in the ongoing battle against wildfires, ultimately saving lives, property, and the environment.

Acknowledgments

The AI modeling and training tools utilized in this project were made available by https://firststep.ai/. Public access to the AI fire detection tool is available at https://bushfire.ai/.

Ethical Statement

This study does not contain any studies with human or animal subjects performed by the author.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

Data available on request from the corresponding author upon reasonable request.

Author Contribution Statement

Leendert Remmelzwaal: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization, Supervision, Project administration, Funding acquisition.

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How to Cite: Remmelzwaal, L. (2023). An AI-Based Early Fire Detection System Utilizing HD Cameras and Real-Time Image Analysis. *Artificial Intelligence and Applications.* https://doi.org/10.47852/bonviewAIA3202975

NV Energy

RESPONSE TO INFORMATION REQUEST

DOCKET NO:	24-12016	**REQUEST DATE:**	02-10-2025
REQUEST NO:	Staff 48	**KEYWORD:**	Wildfire Camera Presentation Slide 27
REQUESTER:	Macatangay	**RESPONDER:**	Hoon, Alexander (NV Energy)

REQUEST:

Reference: PDF “NDPP Wildfire Cameras”

Question: Slide 27 in the PDF “NDPP Wildfire Cameras” (provided by NV Energy as a supplemental response to Staff DR 14) has an “Example” configuration of wildfire cameras (i.e., number, type, infrastructure on which they are installed, etc.). In response to each of the questions below, please provide all the supporting documentation as well as in-depth analytical discussions, including but not limited to quantitative data in executable format, at a level of detail enabling an independent auditor to replicate any calculations in the pertinent software files from start to end.

a. Does NV Energy consider the “Example” configuration an illustrative configuration (rather than a definitive configuration)?

b. Did NV Energy build and apply an optimization model to develop the “Example” configuration?

c. Did NV Energy quantify the implications not only for dollar costs, but also for wildfire detection capability, of the “Example” configuration?

d. Did NV Energy build and apply an optimization model to develop alternative “Example” configurations?

e. Did NV Energy quantify the implications not only for dollar costs, but also for wildfire detection capability, of alternative “Example” configurations?

f. Please email Manny Macatangay remacatangay@puc.nv.gov for any clarification questions.

RESPONSE CONFIDENTIAL (yes or no): No

TOTAL NUMBER OF ATTACHMENTS: None

RESPONSE:

a. Yes, the "Example" configuration presented in Slide 27 of the 2025 PUCN NDPP Wildfire Cameras presentation is illustrative rather than definitive. The configuration serves as a conceptual representation of the potential number, type, and placement of wildfire cameras based on risk assessments, operational needs, and budget estimates. As noted in previous responses to Staff DR 14 and 15, the final configuration will be refined through viewshed analysis conducted by UNR, wildfire risk mapping, and collaboration with BLM and other agencies to maximize coverage while minimizing costs. Adjustments may be made as new data becomes available.

b. No, NV Energy did not use a formal optimization model to develop the "Example" configuration. In the future, the configuration will be informed by the optimization model developed through:
• Wildfire Risk Mapping: Using Technosylva and federal/state agency data to determine high-risk fire zones.
• Viewshed Analysis: Conducted in collaboration with UNR to maximize camera coverage while minimizing gaps (see Staff DR-15 response).
• Infrastructure Considerations: Leveraging existing NV Energy and WISP infrastructure to reduce costs while ensuring effective monitoring. This multi-layered data-driven approach ensures that cameras are placed in the most effective locations based on fire risk, terrain, and network feasibility.

c. Yes, NV Energy has conducted qualitative and cost-based analyses regarding wildfire detection capability and costs for the proposed camera placements.
• Capital and OMAG Costs: Slide 27 of the PUCN Staff Wildfire Cameras Presentation provides a cost breakdown:
o Long-range cameras (NV Energy vs WISP infrastructure)
o Mobile cameras
o Short-range cameras (FireBIRD or similar)
o Estimated and requested budget figures
• Detection Coverage:
o NV Energy’s partnership with UNR, BLM, and ALERTWildfire ensures strategic placement via viewshed analysis to improve situational awareness.
o AI Wildfire Detection & FLIR (infrared) technology will enhance fire detection capabilities, including nighttime monitoring (as described in previous Staff DR-15 responses). While exact dollar-to-detection efficiency metrics are difficult to quantify, NV Energy follows industry best practices (similar to PG&E, SCE, and SDG&E) to maximize fire detection coverage while minimizing costs.

d. No, NV Energy did not develop alternative configurations. The example is illustrative to see a potential combination of cameras NV Energy could deploy with approved funding. See response for part B above for future optimization model.

e. No. Please see response to part C above.

SUPPLEMENT
NV Energy
RESPONSE TO INFORMATION REQUEST

DOCKET NO:	24-12016	**REQUEST DATE:**	02-05-2025
REQUEST NO:	Staff 14 Supplement	**KEYWORD:**	Meeting on Fire Camera Placement
REQUESTER:	Macatangay	**RESPONDER:**	Hoon, Alexander (NV Energy)

REQUEST:

Reference: page 32 of 313

Question: The Narrative says that "[t]he suggested fire camera placement for this request includes: 30 long-range wildfire cameras, with 25 placed in the North and five in the South; Three long-range mobile cameras, with two placed in the North and one placed in the South; 20 short-range cameras, with 10 placed in the North and 10 placed in the South" (see page 32 of 313). Please email Manny Macatangay remacatangay@puc.nv.gov to arrange a meeting with Staff to discuss the "suggested fire camera placement;" the costs associated with the proposed procurement and configuration (i.e. location, size, features, capabilities, etc.) of planned cameras; the costs associated with the actual procurement and configuration (i.e. location, size, features, capabilities, etc.) of existing cameras; as well as any other material related to the matter of existing or proposed camera procurement and configuration (i.e. location, size, features, capabilities, etc.). The level of detail provided in this discussion should enable an independent auditor to replicate any calculations in the relevant software files from start to end. Please note that such a meeting complements, but does not substitute for, a complete written response to other data requests covering related themes.

RESPONSE CONFIDENTIAL (yes or no): No

TOTAL NUMBER OF ATTACHMENTS: None

ORIGINAL RESPONSE:

Email has been sent to Manny Macatangay to setup a meeting on February 5, 2025.

SUPPLEMENTAL RESPONSE:

RESPONSE CONFIDENTIAL (yes or no): No

ATTACHMENT CONFIDENTIAL (yes or no): No.

TOTAL NUMBER OF ATTACHMENTS: One (zipped)

RESPONSE:

Meeting with Staff was conducted on 2-5-24. Slides that were presented at the meeting are attached as 24-12016 Staff 14 Supp Attach 01.

NVEnergy

NDPP Wildfire Cameras PUCN Staff Meeting

Danyale Howard
Director, Natural Disaster Protection

Alex Hoon
Principal Meteorologist
Natural Disaster Protection

Dan Zaccagnino
Senior Project Manager
Natural Disaster Protection

Bill Savran
Associate Director
UNR, Nevada Seismological Lab

Response to Docket 24-12016, Staff DR-14

The Narrative says that "[t]he suggested fire camera placement for this request includes: 30 long-range wildfire cameras, with 25 placed in the North and five in the South; Three long-range mobile cameras, with two placed in the North and one placed in the South; 20 short-range cameras, with 10 placed in the North and 10 placed in the South" (see page 32 of 313). Please email Manny Macatangay remacatangay@puc.nv.gov to **arrange a meeting with Staff to discuss the "suggested fire camera placement;" the costs associated with the proposed procurement and configuration (i.e. location, size, features, capabilities, etc.) of planned cameras; the costs associated with the actual procurement and configuration (i.e. location, size, features, capabilities, etc.) of existing cameras; as well as any other material related to the matter of existing or proposed camera procurement and configuration (i.e. location, size, features, capabilities, etc.).** The level of detail provided in this discussion should enable an independent auditor to replicate any calculations in the relevant software files from start to end. Please note that such a meeting complements, but does not substitute for, a complete written response to other data requests covering related themes.

- Invitees: Howard, Danyale (NV Energy); Hoon, Alexander (NV Energy) Zaccagnino, Daniel (NV Energy); Fremeau, Paul (NV Energy); William H Savran (UNR); Rafael Emmanuel Macatangay (PUCN); Ramirez, Carlos (NV Energy); Harrell, Jane (NV Energy); John Brownrigg (PUCN); Karen Olesky (PUCN); Andrew Greene (PUCN); Kimberly Burakowski (PUCN);

PUCN Staff Meeting Agenda

- NDPP Situational Awareness Program Overview
- Methodology for Wildfire Camera Placement
- Partnership with ALERTWildfire Network-
  - UNR Seismology Lab, BLM, NV Energy, Tahoe utilities
- Transition to ALERTWest platform w/ A.I. Wildfire Detection
- UNR Seismo Lab's Role
- Overview, Costs -- Long Range Cameras and Mobile Cameras
- Overview, Costs -- Short Range Cameras
- First Amendment Budget
- Questions

NDPP Situational Awareness

- The safety of our customers, our employees and the environment is NV Energy's highest priority.

- Changes in the climate and environment are contributing to an increased risk of wildfires and other natural disasters in Nevada, like those seen in other Western states.

- NV Energy has been working to make our electric grid more resilient in order to help protect our customers and the environment from the risk of natural disasters.

- Situational Awareness is a key part of this program, which includes wildfire cameras and fire detection.

Overview: Natural Disaster Protection Plan

The company's goal is to mitigate risk from natural disasters while minimizing Public Safety Outage Management occurrences. Major components of the NDPP include:

- RISK-BASED DECISION MAKING
- SITUATIONAL AWARENESS
- OPERATIONAL PRACTICES
- EMERGENCY RESPONSE & PUBLIC SAFETY OUTAGE MANAGEMENT
- VEGETATION MANAGEMENT
- CONDITIONAL AWARENESS
- GRID RUGGEDIZATION AND SYSTEM HARDENING
- COMMUNITY OUTREACH AND ENGAGEMENT

- Information from situational awareness equipment, such as weather stations and wildfire cameras, can provide valuable information that may assist the Companies before, during, and after natural disaster events.

- Wildfire Cameras provide critical situational awareness that helps during trouble response and improving response time at the Company, as well as helping partner fire agencies to also have improved response time.

First Amendment -- Situational Awareness

- Data-driven approach to reducing wildfire risk
  - Collaboration with partner agencies is THE KEY to our success
  - ALERTWildfire Network (UNR, BLM, NVE)

- 30 Long-Range Wildfire cameras (includes new autonomous cameras) with University of Nevada, Reno
  - 20 NVE Fire Cameras to date
  - 1080P HD Pan-Tilt-Zoom (PTZ) Cameras

- 3 Long-Range Mobile Cameras
  - Similar setup to the permanent Long-Range 1080P HD PTZ setups
  - UNR able to deploy to ongoing wildfire in short notice

- 20 Short-Range Cameras (10 north, 10 south)
  - Such as FIREBird Cameras
  - Autonomous fire detection for short range
  - Doubles as a weather station
  - Solar powered with battery backup

NVE Strategy for Wildfire Camera Placement

Wildfire Risk Mapping

- Use of Federal and State agency risk mapping that assesses wildfire risk based on vegetation, historical fire data, topography, and climate conditions.
- Use of Technosylva Wildfire Risk Mapping to help guide which areas may have the heightened risk based off historical fire weather events and historical outages.

View-Shed Analysis

- Geographic Information System techniques and tools such as ArcGIS, which include visibility analysis methods.
- Application ensures that cameras cover the largest possible area with minimal blind spots, especially in heightened risk areas.

Infrastructure Monitoring

- Stationary long-range PTZ and short-range cameras are strategically placed near utility infrastructure to monitor for wildfires in those areas.
- The three mobile long-range cameras that the Companies are proposing will be available the Companies to monitor ongoing wildfires and fill in any gaps to monitor such wildfires within short notice.

Integration of Weather Station Data

- Weather's influence on wildfire behavior is well researched and documented.
- Application ensures that wildfire cameras are paired with weather stations in areas where fire risk increases due to specific weather conditions (e.g., high wind corridors).

Artificial Intelligence and Fire Detection Models

- Advanced cameras with AI fire detection capabilities are deployed to areas where early detection is critical.

Stakeholder Collaboration

- Public Utility Commission (PUC) regulations and community input for localized insights to the Natural Disaster Protection Plan.
- Application: Collaborative input with the Bureau of Land Management and other fire agencies ensures cameras serve both utility and public needs.

Cost-Benefit Analyses

- Studies collectively suggest that investing in advanced wildfire detection technologies, including satellite systems, UAVs, and ground-based cameras, can offer significant economic benefits by enhancing early detection capabilities and reducing suppression costs.
- Application: Balancing the number and capabilities of cameras with budget constraints.

ALERTWildfire Camera Network

- Collaboration with public safety partners is key.
  - Bureau of Land Management
  - BLM Cameras mounted on NVE infrastructure
- Local, State, and Federal Fire Agencies get to use the wildfire cameras

NATIONAL SYSTEM OF PUBLIC LANDS
U.S. DEPARTMENT OF THE INTERIOR
BUREAU OF LAND MANAGEMENT

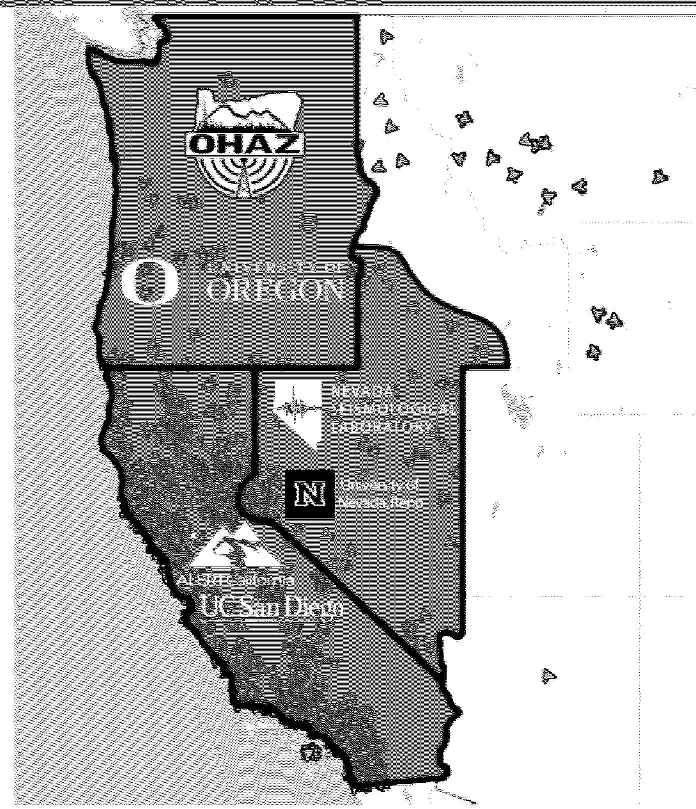
University of Nevada, Reno

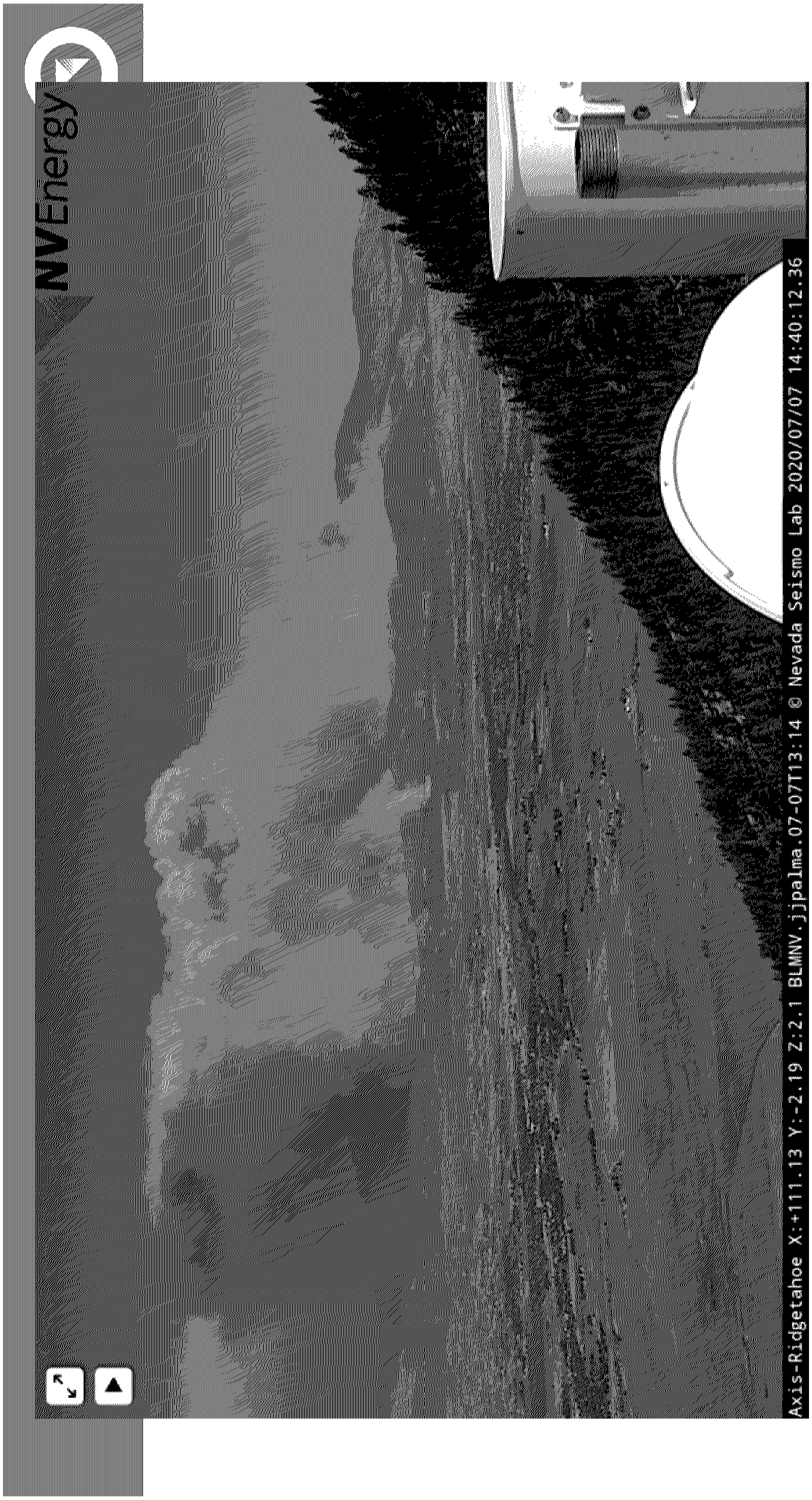
NEVADA SEISMOLOGICAL LABORATORY

NVEnergy®

ALERTWest Platform

- ALERTWildfire Network integrated into ALERTWest in 2024
- Combined three major camera networks
  - University of Nevada
  - University of Oregon
  - UC San Diego

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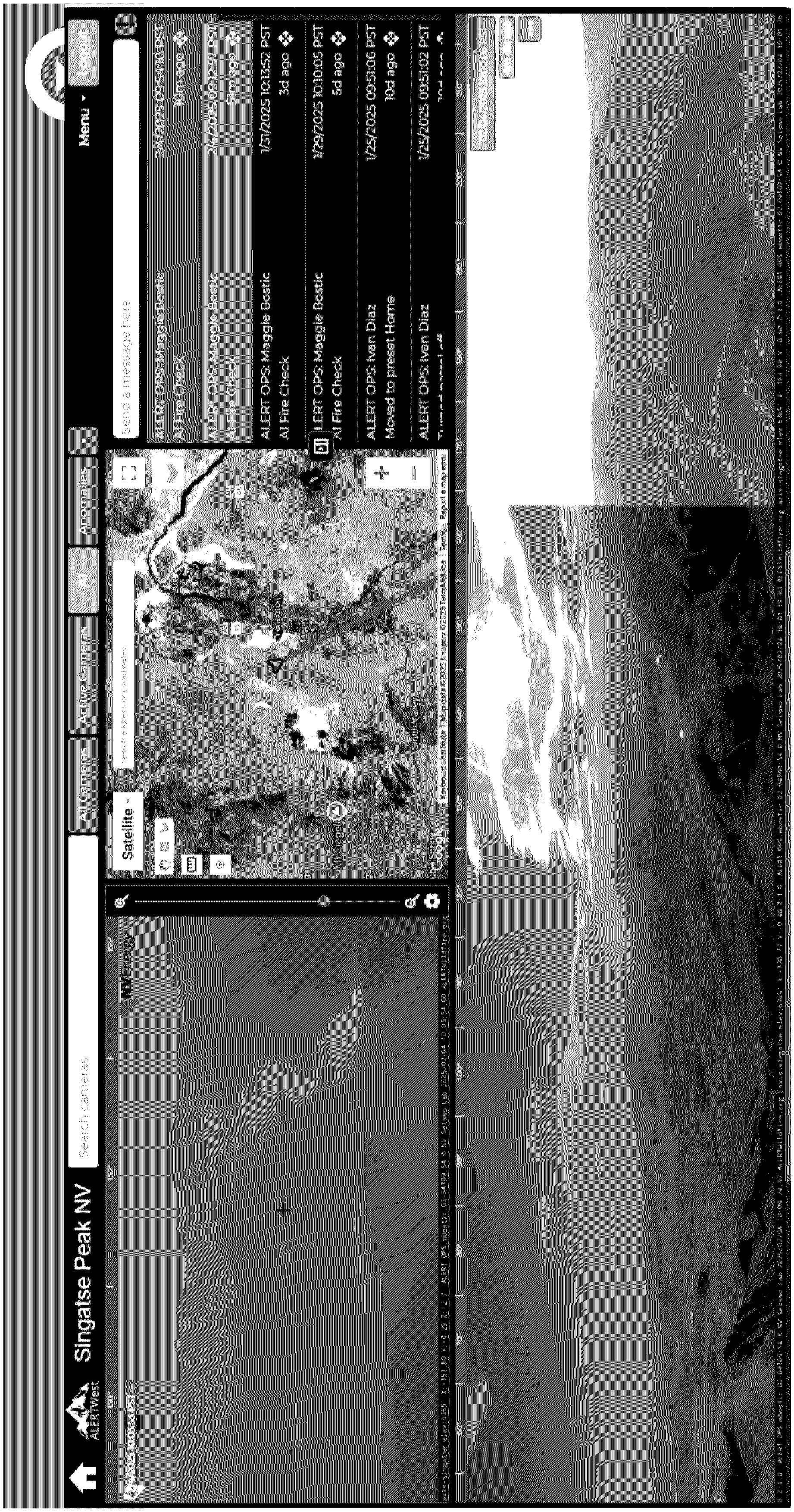
ALERTWest
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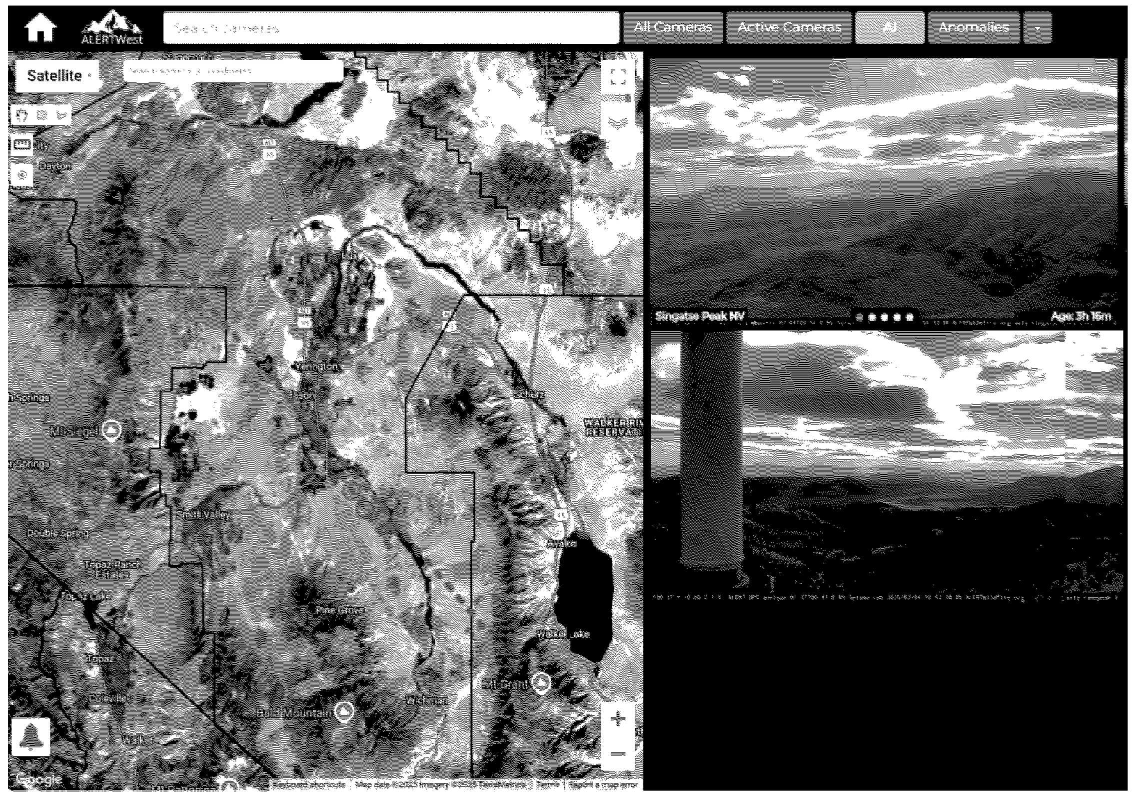
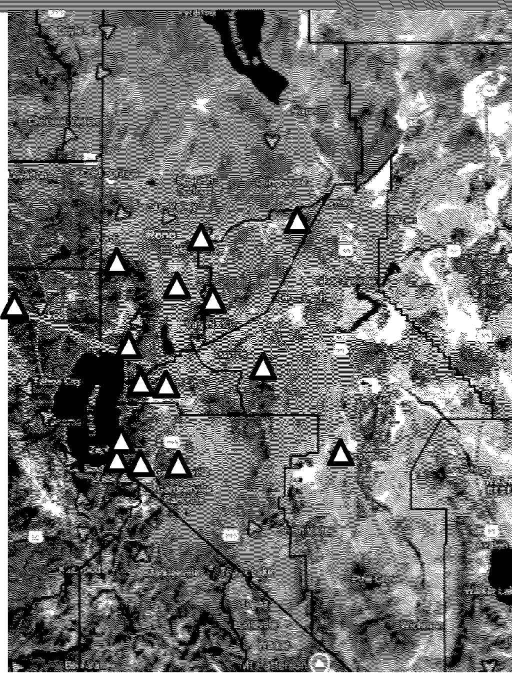
Google

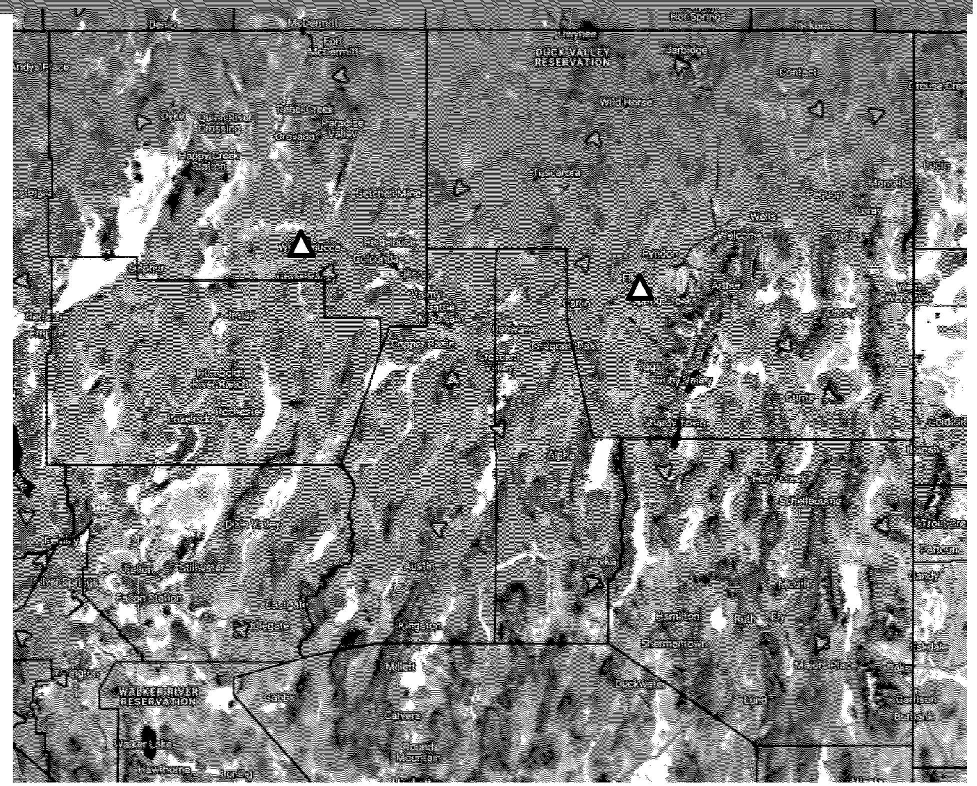
A.I. Wildfire Detection

- Artificial intelligence on all NV Energy, BLM cameras
- Near-Infrared (thermal) fire detection at night
- 24/7 detection of potential new wildfires
- Faster response by partner fire agencies
- Email and text alerts sent to all users



Long Range Wildfire Cameras

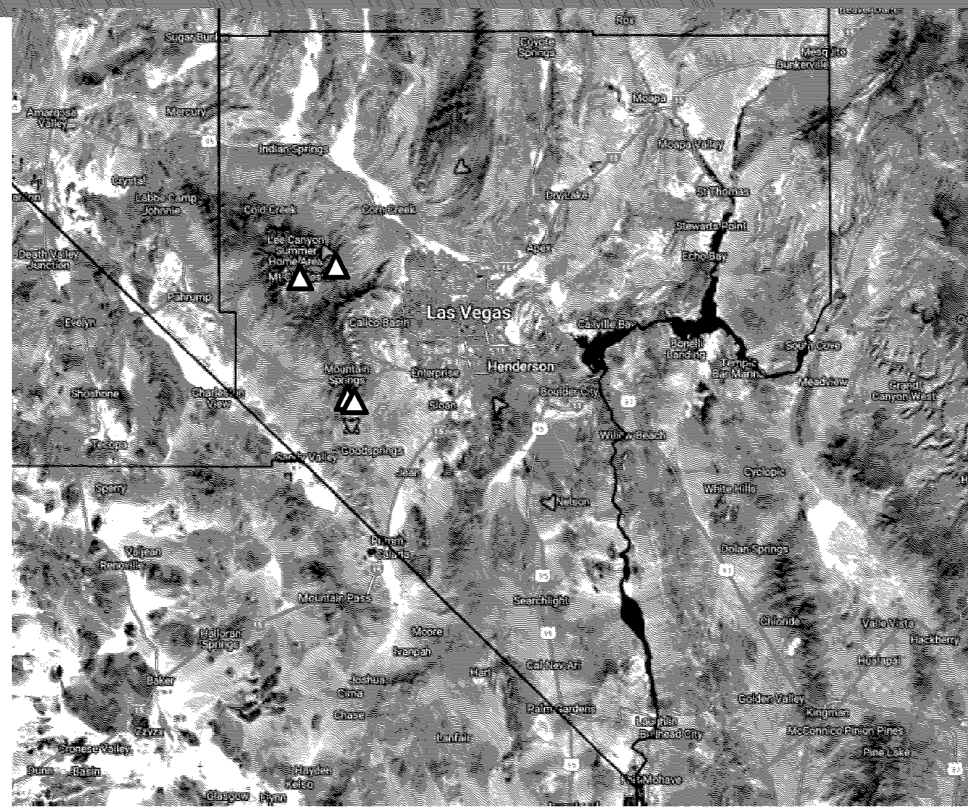




- 16 Wildfire Cameras in Northern Nevada

Long Range Wildfire Cameras

- 4 Wildfire Cameras in Southern Nevada



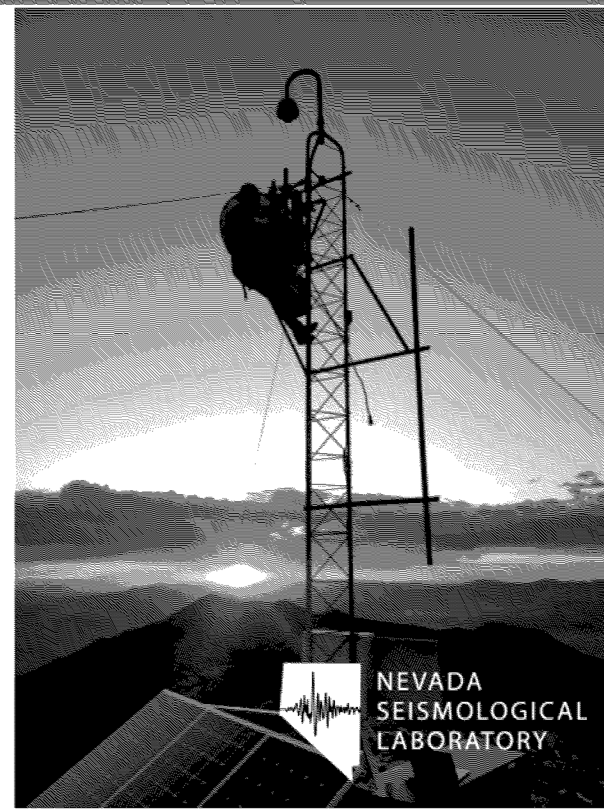
UNR Seismology Lab's Role

Three primary functions:

1. Secure funding for Nevada/Tahoe Fire Cameras

2. Operate private microwave network (NVSciNet) for camera backhaul in remote areas

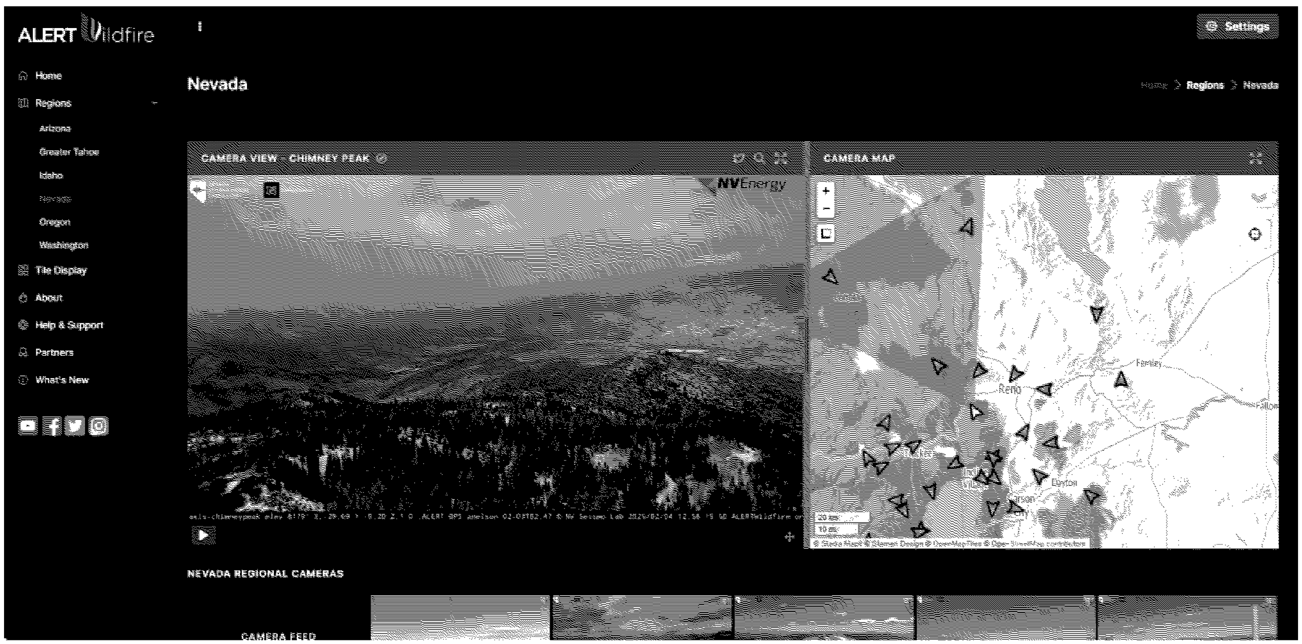
3. Install and maintain fire camera infrastructure and support the ALERTWildfire redundant website



AlertWildfire Network Redundancy

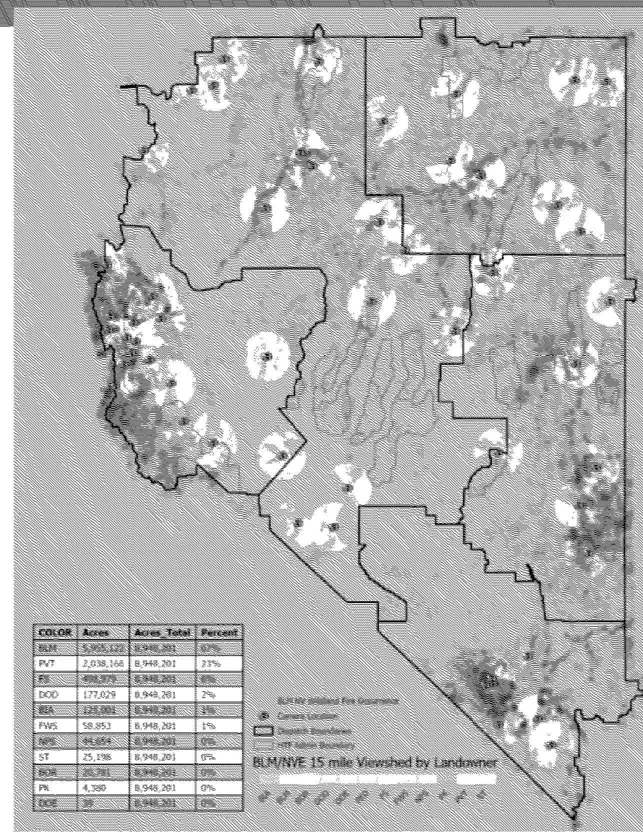
Redundancy through Alert Wildfire (University of Nevada, Reno)

- If there is a major outage on AlertWest, then we will still be able to use our cameras, as well as others on Alert Wildfire.



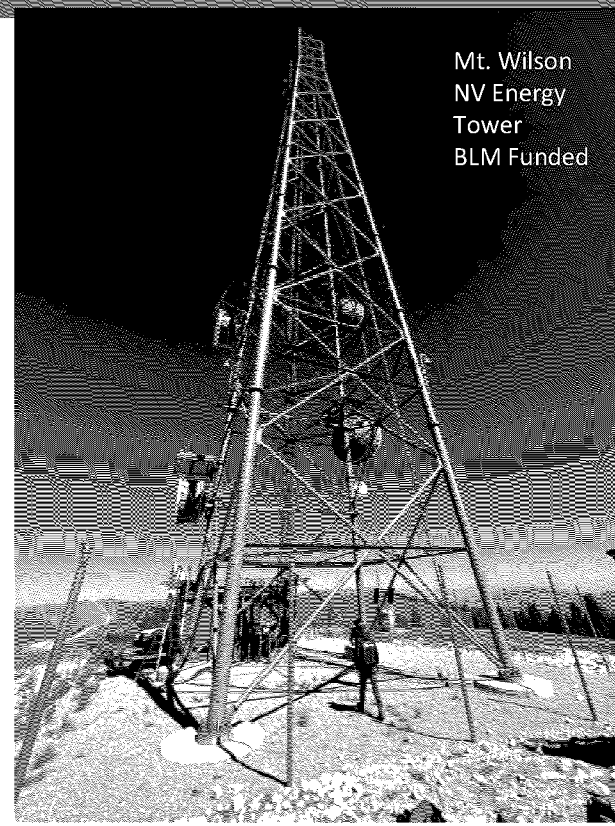
View-Shed Analysis with UNR/BLM

- All BLM and NV Energy Cameras in Nevada
- 15 mile viewshed analysis
- Overlays of historical wildfires
- Working on exact placements
  - Tier 3, 2, 1E, and 1
  - NVE Existing Telecom Towers
  - Existing WISP Towers
- Filling in gaps of coverage, using existing infrastructure first (cheaper)



Costs for Long-Range Cameras

- **Fresh site**
  - Capital Ex: $40,000
  - OMAG:
    - ALERTWest: $6,000/yr
    - Maintenance: (Yr 2+) $5,500/yr
- **Install on NV Energy infrastructure**
  - Capital Ex: $20,000
  - OMAG:
    - ALERTWest: $6,000/yr
    - Maintenance: (Yr 2+) $5,500/yr
- **Install on WISP infrastructure**
  - Capital Ex: $13,000
  - OMAG:
    - ALERTWest: $6,000/yr
    - Backhaul: $6,000/yr
    - Maintenance: (Yr 2+) $1,500/yr



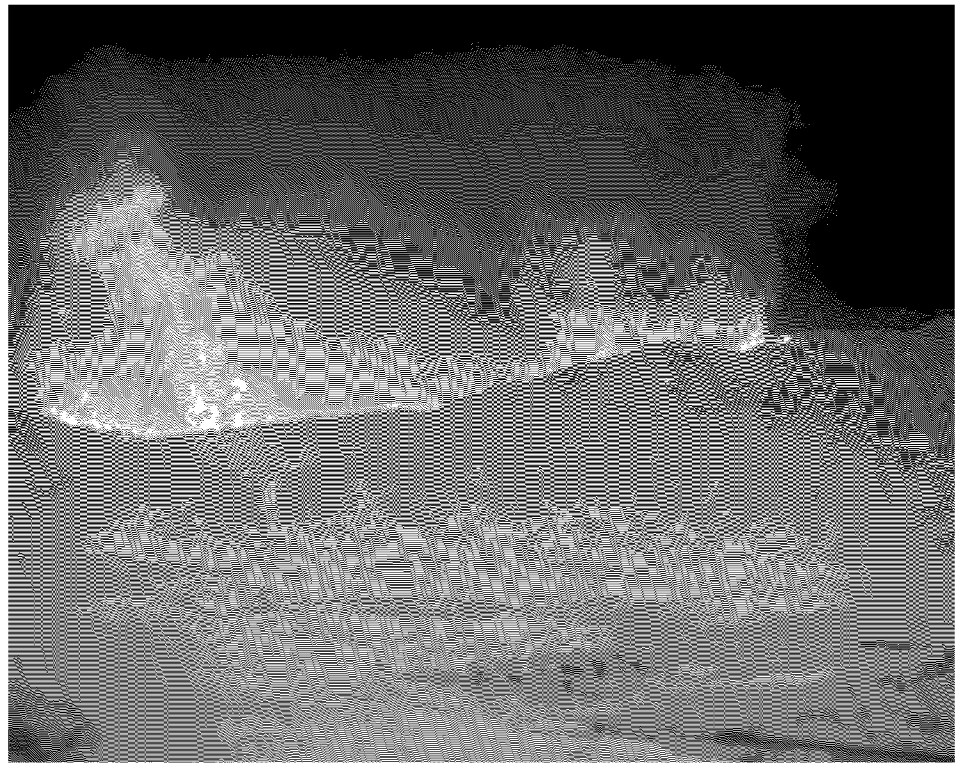
Mobile Long-Range Wildfire Cameras

Mobile Camera Cost w/ FLIR
Capital: $60,000
OMAG: $3,000/yr

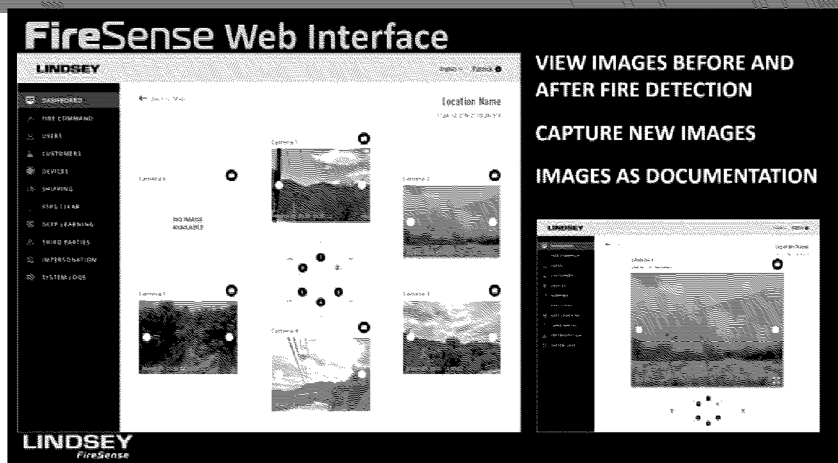
- Camera mounted to trailer that can be towed into location depending on need
- Best way to augment permanent mountain-top cameras with on-demand locations
- Equipped with FLIR camera and Near-infrared cameras to see through smoke
- LiFePO4 batteries to provide power for days during no sunlight

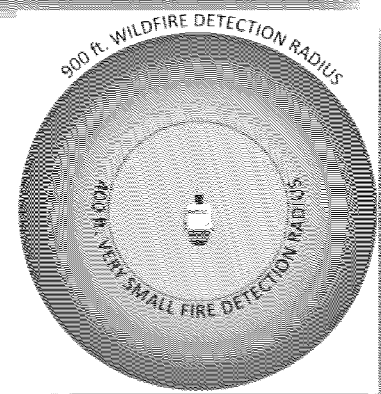
FLIR (Forward Looking Infrared)

- Mobile Long-Range PTZ Camera equipped with FLIR
- Caldor Fire burning over Echo Summit and into the Lake Tahoe Basin
- Image was taken using FLIR during the overnight hours
- FLIR can see through smoke to see where the fire is
- Emergency De-Energization



FIRE*Bird* Cameras





FIREBird Short Range Camera Pilot Project

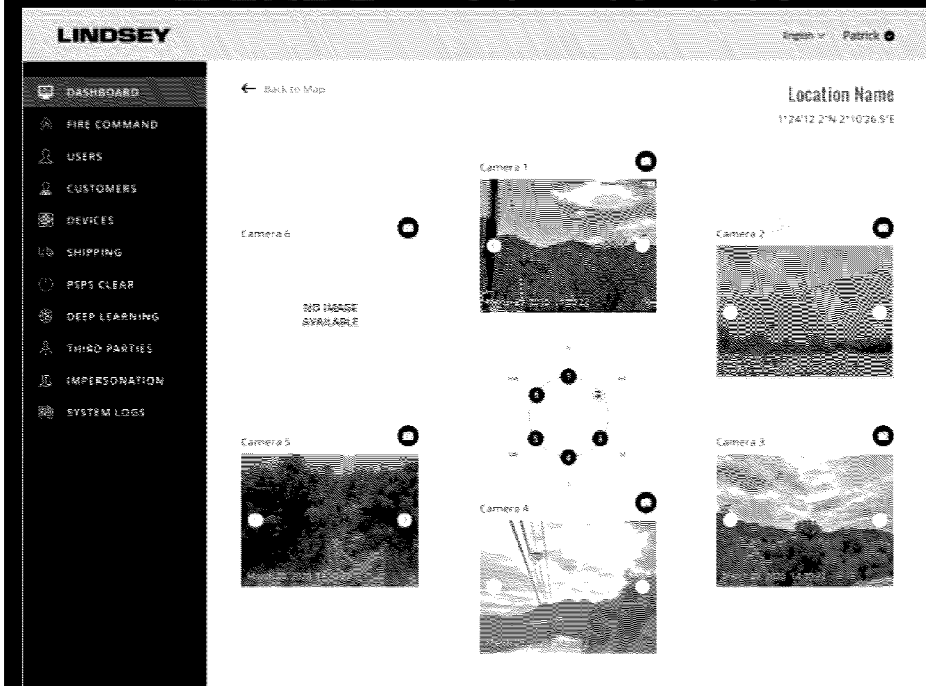
- Capital Ex: $12,500
- OMAG: $2,500/yr

Smaller scale cameras (all directions)

- Infrared (thermal) and visual A.I. -- 24/7 detection
- Built in weather station and cell/satellite capability

FIRE*Bird* Cameras

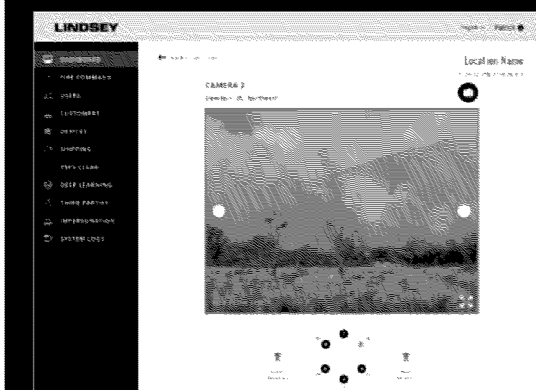
FireSense Web Interface



VIEW IMAGES BEFORE AND AFTER FIRE DETECTION

CAPTURE NEW IMAGES

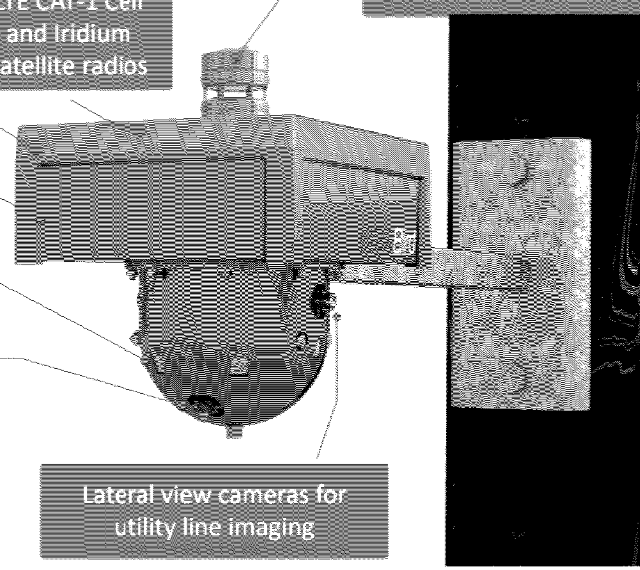
IMAGES AS DOCUMENTATION



LINDSEY
FireSense

FIREBird Cameras

Free Standing FIREBird Device



LINDSEY FireSense

NVE 1st Amendment Budget Request

NV Energy - OMAG Enhanced Fire Season Protocols	2024-2026 Approved Triennial Budget	2024-2026 Forecast	Total First Amendment Request Increase / (Reduction)
NPC			
Situational Awareness - Wildfire Cameras	**199,163**	**300,672**	**101,509**
• Wildfire Cameras - Currently Approved	199,163	174,608	(24,555)
• Wildfire Cameras - Additional	0	126,064	126,064
SPPC			
Situational Awareness - Wildfire Cameras	**1,163,394**	**1,427,322**	**263,928**
• Wildfire Cameras - Currently Approved	1,163,394	960,518	(202,876)
• Wildfire Cameras - Additional	0	466,804	466,804
Grand Total	**1,362,557**	**1,727,994**	**365,437**

NV Energy - Capital Enhanced Fire Season Protocols	2024-2026 Approved Triennial Budget	2024-2026 Forecast	Total First Amendment Request Increase / (Reduction)
NPC			
Situational Awareness - Wildfire Cameras	**389,211**	**755,411**	**366,200**
• Wildfire Cameras - Currently Approved	389,211	389,211	0
• Wildfire Cameras - Additional	0	366,200	366,200
SPPC			
Situational Awareness - Wild Fire Cameras	**1,450,918**	**1,981,918**	**531,000**
• Wildfire Cameras - Currently Approved	1,450,918	1,350,918	-100,000
• Wildfire Cameras - Additional	0	631,000	631,000
Grand Total	**1,840,129**	**2,737,329**	**897,200**

NVE 1st Amendment Budget Request

- Example:
  - 10 Long Range Cameras Installed on NVE Infrastructure
    - Capital Cost: $200k
    - OMAG Cost: $60k
  - 20 Long Range Cameras Installed on WISP Infrastructure
    - Capital Cost: $260k
    - OMAG Cost: $240k
  - 3 Mobile Long-Range Cameras
    - Capital Cost: $180k
    - OMAG Cost: $9k
  - 20 Short Range Cameras
    - Capital Cost: $250k
    - OMAG Cost: $50k

Estimated Capital Cost	Estimated OMAG Cost
$890,000	$359,000

Requested Capital Cost	Requested OMAG Cost
$897,200	$365,437

NV Energy

- Questions and Discussion

NV Energy

RESPONSE TO INFORMATION REQUEST

DOCKET NO:	24-12016	**REQUEST DATE:**	01-14-2025
REQUEST NO:	Staff 16	**KEYWORD:**	Fire Camera Placement
REQUESTER:	Macatangay	**RESPONDER:**	Hoon, Alexander (NV Energy)

REQUEST:

Reference: page 32 of 313

Question: The Narrative says that "[t]he suggested fire camera placement for this request includes: 30 long-range wildfire cameras, with 25 placed in the North and five in the South; Three long-range mobile cameras, with two placed in the North and one placed in the South; 20 short-range cameras, with 10 placed in the North and 10 placed in the South" (see page 32 of 313). Did NV Energy quantify the dollar benefits gained (or dollar costs avoided) of the configuration (i.e. location, size, features, capabilities, etc.) of the "suggested fire camera placement"?

A.If no, please explain why.

B.If yes, please provide supporting documentation, reference materials relied upon, and analytical discussions, including but not limited to quantitative evidence in executable format, at a level of detail enabling an independent auditor to replicate any calculations in the relevant software files from start to end.

C.Please email Manny Macatangay remacatangay@puc.nv.gov for any clarification questions.

RESPONSE CONFIDENTIAL (yes or no): No

TOTAL NUMBER OF ATTACHMENTS: None

RESPONSE:

To date, NV Energy has not been able to quantify the dollar benefits gained or dollar costs avoided by the configuration of the suggested fire camera placement. NV Energy, the Bureau of Land

Management ("BLM"), and University of Nevada have been working to try to quantify this figure, but the Companies can only estimate potential dollar costs avoided based on the potential for a destructive wildfire. Specific benefits are difficult to quantify. For instance, in the September 2024 Davis Fire, the local, state, and federal fire agencies responding were able to use NV Energy fire cameras to deploy resources more efficiently and monitor the wildfire's progress. The Companies were also able to use the wildfire cameras to estimate wildfire locations and the direction of spread to determine circuits to be de-energized by emergency de-energization. If the Davis fire had not stopped where it did, it could have burned into the suburban areas of south Reno, becoming a much more catastrophic wildfire with severe damages in the hundreds of millions.

Given that early wildfire detection results in quicker and more successful fire suppression outcomes, the potential risk mitigated by the implementation of these wildfire cameras is orders of magnitude larger than the cost of the cameras themselves and their upkeep. The cost savings of optimal versus suboptimal camera placement are not ready quantifiable. Rather, NV Energy follows industry best practices in leveraging existing infrastructure for connectivity and power where possible, geographic advantages (i.e., mountaintop sites with significant viewsheds), and relationships with state and local entities and organizations to obtain the greatest camera viewsheds while minimizing expenditure.

The example below presents a very conservative example that assumes wildfire cameras help avoid one small fire. The potential savings associated with wildfire cameras reducing wildfire impacts to the community far outweigh costs even in this conservative example.

Example Calculation (Conservative Estimate)
Scenario: NV Energy wildfire camera system installed in heightened risk areas.
• Cost of Deployment: ~$1,000,000.
o Annual OMAG: ~$500,000/year
• Estimated Benefits:
o Reduced suppression costs: $1M/year.
o Property saved: $5M/year.
o Avoided liability: $10M/event (one event every 5 years).
• Total Annual Benefits: $1M + $5M = $6M/year.
• NPV Calculation (10 years, 5% discount factor):
o NPV = (Annual Benefits × Discount Factor) + Avoided liability – Cost.
o NPV = ($6M × 7.72) + $20M – $11M = $56.32M.

SUPPLEMENT

NV Energy

RESPONSE TO INFORMATION REQUEST

DOCKET NO:	24-12016	**REQUEST DATE:**	02-14-2025
REQUEST NO:	Staff 21 Supplement	**KEYWORD:**	List & Description of Technologies
REQUESTER:	Macatangay	**RESPONDER:**	Hoon, Alexander (NV Energy)

REQUEST:

Reference: page 38 of 314

Question: The Narrative says that “Technology has made a quantum leap since the NDPP was launched nearly five years ago. The industry has converged toward technologies that leverage advanced analytics, artificial intelligence, and increased computing capabilities;” and mentions “AiDash” and “Palantir Foundry” (see page 38 of 314). Q&A 18 of the Prepared Direct Testimony of Alexander Hoon says that “NV Energy will use data from weather stations, wildfire cameras, and advanced weather and wildfire modeling systems to identify the potential for extreme conditions in forecasts and in real-time. The tools that the Companies use to identify extreme conditions include situational awareness dashboards from Cloudfire, wildfire risk modeling from Technosylva, as well as weather station data and wildfire camera imagery from NV Energy and other publicly shared data. By integrating this information, the Companies can make timely decisions about when and where to initiate PSOM.” For each of the questions below, kindly provide comprehensive discussions, including but not limited to references to reliable material as well as quantitative evidence in executable format (at a level of detail enabling an independent auditor to quickly and conveniently replicate any calculations from start to end).

a.Please provide a complete list of technologies in NV Energy’s portfolio of analytical tools for the NDPP.

b.Describe how each of the technologies in (a) is used. For example, are they for realtime monitoring, time ahead (minute, hour, day, week, month, etc.) planning, project management, etc.? In other words, what is the workflow process for each of, and across, them? What decisions do they support? What reports do they produce? Etc.

c. What are the expected operational linkages between AiDash and Palantir Foundry on one hand; and the rest of NV Energy's portfolio of analytical tools for the NDPP on the other?

d. Please email Manny Macatangay remacatangay@puc.nv.gov for any clarification questions.

RESPONSE CONFIDENTIAL (yes or no): No

ATTACHMENT CONFIDENTIAL (yes or no): No

TOTAL NUMBER OF ATTACHMENTS: One (Zipped)

ORIGINAL RESPONSE:
RESPONSE:

a. NV Energy, via the NDPP, utilizes situational awareness technologies that can be classed as either observational or prognostic. Additionally, several analytical tools synergistically combine observational and prognostic data for enhanced awareness and decision support. Observational technologies provide information about the present state of a variable – fuel moisture, relative humidity, wind gust speed, or AI wildfire detections, for example. Prognostic technologies provide a forecast of a given variable or phenomenon – the future state of a weather variable, forecasts of potential fire spread, outage probabilities, or composite risk for a PDZ representing the likelihood of a utility-related wildfire.

NV Energy uses the following observational analytical tools:
• NV Energy Weather Stations (Western Weather Group)
• Long- and short-range Wildfire Cameras (University of Nevada – Reno, AlertWest, FIREBird)
• Fuel moisture sampling and Energy Release Component modeling (Sig-GIS)
• Publicly available weather and fuels observations from sources including, but not limited to, the National Oceanographic & Atmospheric Administration, National Forest Service, etc.

NV Energy utilizes the following prognostic analytical tools:
• Technosylva Wildfire Analyst Tools
• High-resolution WRF Weather Modeling (ADS/Technosylva)
• Cloudfire Fire Weather Dashboard • Pyrecast Weather & Wildfire Forecasts
• Publicly available forecasts for variables associated with weather and wildland fire risk from sources including, but not limited to, the National Oceanographic & Atmospheric Administration, National Forest Service, etc.

The following tools provide enhanced situational awareness and decision support by displaying a synergy of observational and prognostic tools:
• Technosylva Wildfire Analyst Tools - Displays live weather station observations, wildfire camera imagery, and wildfire detections and perimeter observations along with forecasted weather, risk, and wildfire simulations.

• Cloudfire Weather Dashboard - Displays weather forecasts overlaid with actuals (ground truth) for comparative analysis and assessment of forecast performance.

AiDash, once implemented, will leverage merged AI-enhanced environmental and asset data and observations to identify and prioritize vegetation management and maintenance opportunities.

Once implemented, Palantir Foundry will combine observational and prognostic weather and wildland fire risk-related data with enterprise and asset-related data including, but not limited to asset type, age, inspection status, vegetation management variable status, etc. Palantir Foundry provides the ability to connect and integrate disparate datasets on the enterprise level within a single platform, providing the ability to easily derive insights from previously disconnected datasets. It is possible to integrate any of the above-mentioned datasets with Palantir Foundry.

b. Please see attachment 01 for table of technologies used at NV Energy.

c. AiDash and Palantir Foundry are expected to work together to enhance NV Energy's NDPP by integrating and leveraging data for comprehensive situational awareness and decision-making. Palantir Foundry serves as a platform for unifying NV Energy's databases into a single application. AiDash serves as a useful tool which will produce actionable insights in its own right, but will be combined with risk data from Technosylva to further refine risk associated with vegetation contact on powerlines. AiDash will also serve as an input into Palantir Foundry, where AiDash vegetation data can be joined and used synergistically with other NV Energy datasets. Put another way, Palantir Foundry combines this information with other risk factors (e.g., weather conditions, infrastructure vulnerability) to optimize vegetation management strategies and resource allocation. NV Energy's other analytical tools are already utilized in concert to inform mitigations like PSOM and Emergency De-Energization, support the declaration of fire "high" season, initiating Seasonal Fire Mode and FTFM settings, and keeping the Incident Management Team apprised of weather-related risks affecting the Company. Soon, Palantir Foundry will serve as a central, integrated resource for the evaluation of these tools, facilitating even more efficient utilization of these tools.

SUPPLEMENTAL RESPONSE:
SUPPLEMENT : 1
RESPONSE CONFIDENTIAL (yes or no): No

ATTACHMENT CONFIDENTIAL (yes or no): No

TOTAL NUMBER OF ATTACHMENTS: One (Zipped)

RESPONSE:

Supplemental chart included for Staff 21 Part B.

	Historical Data	Real-Time Assessment	1-5 Day Planning	Week Ahead Planning	Months Ahead Planning	Years Ahead Planning
NV Energy Weather Stations	✓	✓	X	X	X	X
Long- and short-range wildfire cameras	✓	✓	X	X	X	X
Fuel Moisture Sampling	✓	✓	✓	✓	X	X
Publicly available weather/ climate/fuels observations & forecasts	✓	✓	✓	✓	✓	X
Technosylva Wildfire Analyst: FireRisk & FireSim	✓	✓	✓	X	X	X
Technosylva FireSight	X	X	X	X	✓	✓
High-Resolution WRF Weather Modeling	✓	✓	✓	X	X	X
CloudFire Fire Weather Dashboard	✓	✓	✓	✓	X	X
Pyrecast Weather & Wildfire Forecasts	X	✓	✓	✓	X	X
AiDash (requested)	X	✓	✓	✓	✓	✓
Palantir Foundry	✓	✓	✓	✓	X	X
Microsoft Azure Data Lake & Machine Learning Tools	✓	✓	✓	✓	✓	✓

NV Energy

RESPONSE TO INFORMATION REQUEST

DOCKET NO:	24-12016	**REQUEST DATE:**	01-21-2025
REQUEST NO:	Staff 20	**KEYWORD:**	Optimize Portfolio of Analytical Tools
REQUESTER:	Macatangay	**RESPONDER:**	Hoon, Alexander (NV Energy)

REQUEST:

Reference: page 38 of 314

Question: The Narrative says that "Technology has made a quantum leap since the NDPP was launched nearly five years ago. The industry has converged toward technologies that leverage advanced analytics, artificial intelligence, and increased computing capabilities" (see page 38 of 314). How does NV Energy manage or plan to manage the various analytical tools it has acquired or may acquire for the NDPP? Put differently, given the "quantum leap" in technology, how does NV Energy plan to optimize its portfolio of analytical tools for the NDPP, accounting for the risks of stranded technology assets, swift obsolescence, evolving requirements, etc.? Kindly provide comprehensive discussions, including but not limited to references to reliable material as well as quantitative evidence in executable format (at a level of detail enabling an independent auditor to quickly and conveniently replicate any calculations from start to end). Please email Manny Macatangay remacatangay@puc.nv.gov for any clarification questions.

RESPONSE CONFIDENTIAL (yes or no): No

TOTAL NUMBER OF ATTACHMENTS: None

RESPONSE:

NV Energy is committed to ensuring alignment with the industry standards by leveraging advanced analytics and technology to reasonably implement the NDPP and protect ratepayers from costs and other impacts associated with catastrophic fire. NV Energy's technology portfolio integrates robust tools and platforms to assess and mitigate wildfire risks across Nevada. Current solutions include our newly developed Microsoft Azure data lake, which uses cloud environment over 20 datasets to power machine learning models to estimate wildfire risk. This data lake was completed in December 2024, and the machine learning modeling is in development as of the first quarter of 2025. Our other technology solutions include the high-resolution weather modeling (WRF) from ADS/Technosylva, wildfire cameras, weather stations, and tools like Technosylva's Wildfire Analyst, CloudFire, and Pyrecast forecasts which provide precise, data-driven insights.

NV Energy addresses risks of obsolescence and stranded technology by continually evaluating tools for compatibility, scalability, and alignment with evolving power industry standards. Contracts are either based on an annual basis or triennial (only Technosylva has a 3 year contract). If a technology that the Companies are using becomes obsolete, the Companies will either discontinue any renewal of contracts, or the Companies will ensure that the renewal of contracts ensures that the technology is aligned with the most current utility industry standards. Additionally, the two meteorologists and the data scientist for NDPP attend industry conferences, workshops, and working groups that discuss the current state of the advanced technologies, including wildfire and weather modeling and analytics, wildfire cameras, weather stations, etc... If the portfolio of technology at NV Energy is falling behind, the Companies will look to add/remove/modify strategies based off industry trends.

For example, upcoming platforms like Palantir Foundry and AiDash will enhance data integration and real-time decision-making for wildfire risk and supporting our vegetation management program, introduces fire incident analysis and improves customer preparedness for pro-active de-energizationes. Redundancy through diverse data sources, including NOAA and the U.S. Forest Service, ensures resilience and are continuously used to cross-validate results and forecast.

NV Energy's approach minimizes risk while maximizing the value of our analytical investments, ensuring NDPP remains adaptable and effective amid technological advances.

NV Energy

RESPONSE TO INFORMATION REQUEST

DOCKET NO:	24-12016	**REQUEST DATE:**	01-14-2025
REQUEST NO:	Staff 18	**KEYWORD:**	Howard Direct V Mapping Corrections
REQUESTER:	Lucban	**RESPONDER:**	Howard, Danyale (NV Energy)

REQUEST:

Reference: Section 2.7 Mapping Corrections, Howard-DIRECT Section V.

Question: With respect to the mapping corrections related to the Mount Charleston and Lake Tahoe areas,

1. Please explain how and when NV Energy (or any applicable consultant) identified these errors.

2. Please explain any controls in place that would ensure NV Energy's (or any applicable consultant) identification of the fire Tier area maps are being recorded and submitted in an NDPP or NDPP amendment appropriately.

3. Please explain whether NV Energy expects further mapping corrections (based on identified errors) to be filed in the context of another amendment to the current triennial plan.

4. Please also explain the process that NV Energy follows or plans to follow to update the risk tiers after approved NDPP projects have been executed.

Please contact Percy Lucban (plucban@puc.nv.gov) or Gaurav Shil (gshil@puc.nv.gov) if there are any questions related to any data request in this batch.

RESPONSE CONFIDENTIAL (yes or no): No

TOTAL NUMBER OF ATTACHMENTS: None

RESPONSE:

1. The map issue was identified by the NDPP team executing hazardous ground fuels and tree trimming. The team identified that Tier 1 is non-contiguous or "checker-boarded" in several areas of the moderate risk areas and that two significant gaps were evident in the high-risk area of Mt. Charleston and Lake Tahoe represented in Figure 5 and Figure 6.

2. NV Energy intends to draft procedures around risk map creation and updates that will include a quality assurance review that includes an operational review and distribution communication for any changes to fire tier boundaries. Creation and management of map procedures will be the responsibility of the proposed Situational Awareness Manager.

3. NV Energy does not expect further mapping corrections to be filed in the context of an amendment to the current triennial plan.

4. As part of the third triennial plan, NV Energy will evaluate the industry standard for updating or revising risk prioritization for areas where past risk mitigation efforts have been executed.

NV Energy

RESPONSE TO INFORMATION REQUEST

DOCKET NO:	24-12016	**REQUEST DATE:**	03-19-2025
REQUEST NO:	Staff 59	**KEYWORD:**	Section 2.7 Anomaly
REQUESTER:	Lucban	**RESPONDER:**	Costello, Brian (NV Energy)

REQUEST:

Reference: Section 2.7, Mapping Corrections

Question: For the fire tier map corrections, please explain in detail the GIS anomaly referenced in Section 2.7. As part of this response, describe what the anomaly was, how it was caused, how it was identified, when it was identified, and by whom (e.g. position title of NV Energy personnel or outside consultant).

Please contact Percy Lucban with any clarification questions pertaining to the above request.

RESPONSE CONFIDENTIAL (yes or no): No

TOTAL NUMBER OF ATTACHMENTS: None

RESPONSE:

For Figure 5 in Section 2.7, the GIS anomaly was that the Canyon 3401 line segment shown in the cross-hatched area lies within Tier 1, but this segment was not included in the risk tier maps when they were originally prepared in 2019. For Figure 6 in Section 2.7, the GIS anomaly was that the Steamboat 212 line segment shown in the cross-hatched area lies within Tier 2, but this segment was not included in the risk tier maps when they were originally prepared in 2019. As noted in the October 2, 2024, email from Scott Lucas that was provided in the Companies' response to Staff DR 60, Attachment 1, Truckee Meadows Fire Protection District notified the Companies on October 1, 2024, that they were about to perform work outside of a tiered area. This notification was received by Scott Lucas, Fire Prevention Officer at NV Energy, and was related to the Steamboat 212 line segment shown in Figure 6. As noted in the October 3, 2024, email from Emma Davis that was provided in the Companies' response to Staff DR 60, Attachment 1, the Canyon 3401 line segment shown in Figure 6 was identified at about the same time. Identification of this line segment was made by Mark Regan, Fire Mitigation Specialist at NV Energy.

NV Energy

RESPONSE TO INFORMATION REQUEST

DOCKET NO:	24-12016	**REQUEST DATE:**	03-18-2025
REQUEST NO:	Staff 56	**KEYWORD:**	BTGR Funded Mapping Corrections
REQUESTER:	Lucban	**RESPONDER:**	Costello, Brian (NV Energy)

REQUEST:

Reference: Section 2.7, Mapping Corrections

Question: For the fire tier map corrections, please explain whether NV Energy has performed any NDPP-related work in these areas. If NV Energy has performed NDPP-related work in these areas, please identify the map-corrected area and explain the program area in which the funds were spent and provide actual and/or estimated costs by NDPP program and year.

Further, please explain whether NV Energy has performed any non-NDPP (BTGR funded) related work in these areas. If NV Energy has performed non-NDPP related work in these areas, please identify the map-corrected area and explain the type of work performed, a summary explanation of who performed the work, and provide the actual and/or estimated costs by project/program/work order and year. Please contact Percy Lucban with any clarification questions pertaining to the above request.

RESPONSE CONFIDENTIAL (yes or no): No

TOTAL NUMBER OF ATTACHMENTS: None

RESPONSE:

The Companies did perform NDPP related work in the area shown in Exhibit B First Amendment, Figure 6. Lake Tahoe Area Map Correction. Pole grubbing and ROW clearing was performed in Zone 1 and Zone 2 on a portion of the Steamboat 212 line. An estimated $17,300 was spent in 2023 and $76,700 in 2024. The Companies interpret non-NDPP (BTGR funded) work to mean what the Companies typically reference as NDPP GRC work, which is work for which recovery is not sought through the regulatory asset but rather through a general rate case (BTGR funded). The Companies did not perform any of this type of work. The Companies do not interpret this request to include the normal construction and maintenance work performed over the entire history of the involved line segments as this would be out of scope under the instant Docket.

NV Energy

RESPONSE TO INFORMATION REQUEST

DOCKET NO:	24-12016	**REQUEST DATE:**	01-10-2025
REQUEST NO:	BCP 1-02	**KEYWORD:**	NPC/SPPC OMAG, Sierra Capital & Underspend
REQUESTER:	BCP	**RESPONDER:**	Philavanh, ShazzyLynn

REQUEST:

Reference: NDPP 2024-2026 Current Forecast

Question: Regarding Exhibit B of the First Amendment for the NDPP Plan, please confirm or deny the following, and if deny please provide an explanation:

1) Table 5. Nevada Power OMAG – Adjusted Labor Resources for Approved NDPP Programs state “2024-2026 Current Forecast” and include a Grant Total of $26,737,712. Without the current amendment to the NDPP application, is this the dollar amount Nevada Power Company d/b/a NV Energy (“NPC”) and Sierra Pacific Power Company d/b/a NV Energy (“SPPC” and collectively the “Utilities”) are currently forecasted to spend for NPC OMAG expenses (which is a ($6,745,502) decrease from the originally approved budget)?

2) Table 6. Sierra OMAG – Adjusted Labor Resources for Approved NDPP Programs state “2024-2026 Current Forecast” and include a Grant Total of $160,448,781. Without the current amendment to the NDPP application, is this the dollar amount the Utilities are currently forecasted to spend for SPPC OMAG expenses (which is a ($8,029,196) decrease from the originally approved budget)?

3) Table 7. Sierra Capital – Adjusted Labor Resources for Approved NDPP Programs state “2024-2026 Current Forecast” and include a Grant Total of $94,716,790. Without the current amendment to the NDPP application, is this the dollar amount the Utilities are currently forecasted to spend for SPPC capital expenses (which is a ($11,405.503) decrease from the originally approved capital budget)?

4) Without any amendments, are the Utilities currently forecasted to underspend the NDPP by ($26,180,201) according to the sums of Table 5 of ($6,745,502), Table 6 of ($8,209,196), and Table 7 of ($11,405,503)?

RESPONSE CONFIDENTIAL (yes or no): No

TOTAL NUMBER OF ATTACHMENTS: None

RESPONSE:

Without the NDPP First Amendment requests, the projected underspend to the NDPP Triennial budget is the following: Nevada Power Company (OMAG) - ($6,745,502), Sierra Pacific Power Company (OMAG) - ($8,029,196), Sierra Pacific Power Company (capital) ($11,405,503), totaling ($26,180,201).

NV Energy

RESPONSE TO INFORMATION REQUEST

DOCKET NO:	24-12016	**REQUEST DATE:**	12-20-2024
REQUEST NO:	Staff 09	**KEYWORD:**	tables 5, 6, 7 NPC SPPC OMAG, SPPC Capital labor resources, budgetary forecast
REQUESTER:	Shil	**RESPONDER:**	Howard, Danyale

REQUEST:

Reference: Tables 5, 6 and 7

Question: (1) Please describe in detail the reasoning for increase and decrease in budgetary forecast for each approved NDPP program.

(2) Please describe in detail the impact on the related NDPP risk tracking metric or NDPP risk in general (if there is no related metric) because of the change in budgetary forecast for each approved NDPP program.

(3) Please confirm that the budgetary reductions for the approved NDPP programs are permanent and no budget increase for these approved programs will be requested in future NDPP filings. If not, please share the annual budgetary estimates included in the 10-year business plan and reasoning for all future increases.

Please contact Percy Lucban (plucban@puc.nv.gov) or Gaurav Shil (gshil@puc.nv.gov) if there are any questions related to any data request in this batch.

RESPONSE CONFIDENTIAL (yes or no): No

ATTACHMENT CONFIDENTIAL (yes or no): No

TOTAL NUMBER OF ATTACHMENTS: One (Zipped)

RESPONSE:

1. 24-12016 - Staff 9 – Attach 01 provides the plan forecast for each approved OMAG and Capital program at the NV Energy level. Variances for the underspend are as follows:

Inspections, Patrols and Corrections – The Companies gained cost efficiencies through new contractual rates for both patrols and inspection services as well as repair of the OMAG corrections. This forecast is not expected to change.

PSOM – The forecast is consistent with the triennial budget.

Risk Based Approach – The forecast is trending at approximately $200,000 over plan budget due to the increase in the cost of generators installed at Kyle Canyon during fire season.

Situational Awareness – The minor variance is attributable to an increased monthly service costs for the weather stations, which is mostly offset by the decrease in monthly service costs for the fire cameras.

Vegetation Management – The forecast is underspent due to limited work performed during 2024 for two reasons. The transition of fire agencies to the new master services professional agreement resulted in a gap in time in which little to no work was performed due to the processing of the new contracts. Secondly, the increased fire season limited work in the high fire risk areas, limited by Red Flag Days and limited work hours imposed by forest supervisors. Additionally, some fire agencies performing ground fuels work were re-assigned to fight fires in other locations and states.

24-12016 - Staff 9 – Attach 02 provides the plan forecast for each approved Capital program. Variances for the underspend are as follows:

Risk Based Approach – The forecasted underspend is attributable to nominal $33,000 fluctuation in estimated costs versus actual costs.

Situational Awareness – The forecasted underspend is attributable to a decrease in the cost of fire cameras.

System Hardening – The forecasted underspend in system hardening is attributable to a delay in the Phase 2 undergrounding plan and substation ruggedization. The Companies will be unable to "catch up" from those delays due to the lead-times for permits and the duration of short seasonal construction. These programs will extend, in part, beyond the current triennial plan. Tree attachment removals, estimated for a completion rate of 80 per year, were delayed due to design resource limitations. The Companies plan to "catch up" the tree removal count with the design resources requested in this amendment filing.

A notable increase in the system hardening forecast is attributable to the Mt. Charleston rebuild. The increase corrects the overstated budget adjustment the Companies performed as part of Compliance 2.

2. Impacts related to plan performance are referenced in response number 1. Of the budget variances discussed above, the two areas where the variance would most likely have a material effect on risk is the vegetation management work that was delayed in 2024 and the system hardening delays. With the transition to the new fire agencies contracts, the Companies anticipate resuming vegetation management consistent with the planned cycles to the extent conditions in the coming fire seasons permit that to occur. With respect to the system hardening, the Companies anticipate that those measures will be completed, but on an extended time table for the reasons explained above. To reiterate, undergrounding and substation ruggedization will extend, in part, beyond the current triennial plan.

Notably, however, a significant amount of additional risk reduction work was completed beyond scope of the NDPP. Out of scope work includes overhead rebuilds that exceeded total anticipated milestones, expulsion fuse replacements that were accelerated beyond the current NDPP forecast and all FTFM capability performed during 2024 and anticipated to be performed during 2025 and 2026.

3. The scope for future triennial plans has not been performed. Therefore, future costs are not available.

Docket #24-12016
Staff 9 - Attach 01

NV Energy - OMAG Approved NDPP Programs Currently	2024-2026 Approved Triennial Budget	2024-2026 Current Forecast	2024-2026 Forecast Incremental Labor Resource Plan	Total 2024-2026 First Amendment Forecast	Total First Amendment Request Increase / (Reduction)
Inspections, Patrols, Corrections	**30,885,600**	16,836,182	72,500	**16,908,682**	**(13,976,918)**
Public Safety Outage Management	**7,782,715**	7,782,715	251,605	**8,034,320**	**251,605**
Risk Based Approach	**13,632,937**	13,883,410	4,419,019	**18,302,429**	**4,669,492**
Situational Awareness	**1,789,486**	1,853,142	0	**1,853,142**	**63,656**
System Hardening	**12,287,530**	11,248,121	72,500	**11,320,621**	**(966,909)**
Vegetation Management	**135,582,922**	135,582,922	5,187,721	**140,770,643**	**5,187,721**
Grand Total	**201,961,191**	**187,186,493**	**10,003,345**	**197,189,838**	**(4,771,353)**

Docket #24-12016
Staff 9 - Attach 02

NV Energy - Capital Currently Approved NDPP Programs	2024-2026 Approved Triennial Budget	2024-2026 Current Forecast	2024-2026 Forecast Incremental Labor Resource Plan	Total 2024-2026 First Amendment Forecast	Total First Amendment Request Increase / (Reduction)
Risk-Based Approach	**45,790**	12,152	0	**12,152**	**(33,638)**
Situational Awareness	**1,840,129**	1,740,129	0	**1,740,129**	**(100,000)**
System Hardening	**142,375,697**	133,796,133	4,735,110	**138,531,242**	**(3,844,455)**
Grand Total	**144,261,616**	**135,548,414**	**4,735,110**	**140,283,523**	**(3,978,093)**

NV Energy

RESPONSE TO INFORMATION REQUEST

DOCKET NO:	24-12016	**REQUEST DATE:**	03-13-2025
REQUEST NO:	Staff 53	**KEYWORD:**	Mapping Correction Budget and Forecasting
REQUESTER:	Lucban	**RESPONDER:**	Costello, Brian (NV Energy)

REQUEST:

Reference: Section 2.7 Mapping Corrections, Howard-DIRECT at Q&A 45

Question: In her direct testimony at Q&A 45, Ms. Howard explains that "the Companies are not requesting additional funding to address these changes currently. Work for these areas will be prioritized among other planned work such as patrols and inspections, vegetation management, and assessment for conversion to a covered conductor alternative where applicable." Given this, please answer the following:

1. Please explain whether NDPP work specific to these additional areas was previously budgeted in a prior docket. If so, please provide the docket number and any citations to the Record as well as an explanation as to whether the budgeted work was approved by the Commission. If the work for these additions was approved by the Commission, please provide the reference or citation from a Commission Order.

2. If NDPP work specific to these additional areas was not previously budgeted and approved by the Commission, please explain what the forecasted cost differential to perform this work would be. Provide a detailed breakdown by NDPP program and program year for the work in the corrected and additional mapping areas.

Please contact Percy Lucban with any clarification questions pertaining to the above request.

RESPONSE CONFIDENTIAL (yes or no): No

TOTAL NUMBER OF ATTACHMENTS: None

RESPONSE:

1. NDPP work in these areas was not previously budgeted in a prior docket.

2. If these additional areas are approved by the Commission, there would be NDPP work to perform under three of the current programs including 1) Vegetation Management, 2) Fire Tier Patrols Inspections, and Corrections, and 3) Non-Expulsion Fuse Replacement. The Companies have not yet developed a work schedule or cost forecast for the work in those areas. If Commission approval is received in 2025, the only immediate work that would be required under the current NDPP would be the annual line patrol of the new Tier 2 area in 2026. The estimated cost to perform this additional patrol work is approximately $1,100.

AFFIRMATION

Pursuant to the requirements of NRS 53.045 and NAC 703.710, PERCIVAL O. LUCBAN, states that he is the person identified in the foregoing prepared testimony and/or exhibits; that such testimony and/or exhibits were prepared by or under the direction of said person; that the answers and/or information appearing therein are true to the best of his knowledge and belief; and that if asked the questions appearing therein, his answers thereto would, under oath, be the same.

I declare under penalty of perjury that the foregoing is true and correct.

Date: 4/3/25

PERCIVAL O. LUCBAN