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The effects and financial impacts of wildfire smoke on solar photovoltaic power production in Alberta, Canada

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Abstract

As reliance on solar photovoltaic (PV) generation grows, particularly in Alberta, accounting for the impact of wildfire smoke on solar energy production is crucial. This is particularly relevant in regions with high PV generation potential, such as Alberta, as they are often more vulnerable to frequent and intense wildfires. This study quantifies PV energy losses and financial impacts due to wildfire smoke in Alberta, using fine particulate matter 2.5 ($PM_{2.5}$) as a proxy for smoke pollution. Historical weather and $PM_{2.5}$ data, along with simulated PV production from actual completed, proposed, and under-construction projects, are used to train and test the model. The simulated data is validated against real production data. The six-year study (2018–2023) covers major wildfire years and employs machine learning techniques, particularly random forest regression, to isolate the effects of $PM_{2.5}$ on solar production. Financial losses are estimated in Canadian dollars, adjusted for inflation to December 2023.

Results show a PV production decline of up to 6.3% at a single solar site over six years, with an overall average reduction of 3.91% under severe conditions. The cumulative impact led to a 0.19% average generation loss, equating to over $4.5 million in financial losses. Higher smoke levels consistently correlate with greater solar energy losses, aligning with findings from other regions. The results of this study enhance our understanding of climate change impacts on solar energy, highlighting wildfire smoke as a relevant factor. As PV adoption expands, these findings offer valuable insights for decision-makers and operational planners, emphasizing the need for strategies to mitigate smoke-related disruptions and ensure energy reliability.

Keywords Photovoltaic production; Wildfires; $PM_{2.5}$; Financial impact; Random forest; Solar power.

JEL: C55, N72, P18, Q42, Q54

1 Nomenclature

Abbreviations	
AESO	Alberta Energy System Operator
AUC	Alberta Utilities Commission
ANN	Artificial Neural Networks
BC	British Columbia
CAAQS	Canadian Ambient Air Quality Standards
DL	Deep Learning
FWI	Fire Weather Index
MSE	Mean Squared Error
$PM_{2.5}$	Fine particulate matter with a diameter of 2.5 micrometers or smaller measured in µg/m³ (micrograms per cubic meter)
POWER	NASA Langley Research Center Prediction of Worldwide Energy Resource
PV	Photovoltaic
R^2	The coefficient of determination
RFR	Random Forest Regression
SAM	System Advisory Model
GHI	Global Horizontal Solar Irradiance
SVR	Support Vector Regression
XGB	XGBoost

2 Introduction

In 2023 Canada experienced its most destructive wildfire season on record with 15 million hectares burned - more than double the previous record of 6.7 million hectares in 1989 and seven times the historical annual average of 2.1 million hectares [1, 2]. This area, equal to 4% of Canada's forests [1, 2], and 1.7% of its land, surpasses the size of more than half the countries in the world [3]. Wildfires in 2023 exhibited unusually extreme behaviors, including "pyro-tornados" and pyrocumulonimbus events -thunderstorms generated by the intense heat of wildfires - that can produce lightning and ignite additional fires [1, 4]. These extreme fire events not only cause devastating losses locally, but also lead to far-reaching impacts on air quality, particularly through the transport of wildfire smoke.

Air pollution from wildfires is often transported downwind over vast distances, and can remain in the atmosphere for months [5, 3]. In some cases, smoke plumes have been observed to circumnavigate the earth [6]. The smoke from Canadian wildfires in 2023 had far-reaching impacts, affecting not only nearby communities, but also major population centers over 1000 km away, such as New York, where the smoke dramatically blocked out the sun, leading to the worst $PM_{2.5}$ levels in half a century [3]. In Alberta, the 2023 fires led to a provincial state of emergency with 2.7 million hectares burned [2]. $PM_{2.5}$, one of wildfire smoke's primary by-products, is the largest contributor to poor air quality events in Alberta [7, 8], emerging as a critical air quality issue.

The 2023 fire season demonstrates what has already been proven in the literature. Fire weather, encompassing weather conditions favourable for wildfires and impacting fire behaviour [9], is worsening in severity [10, 11, 12]. For instance, mean May-October temperatures for 2023 in Canada were 2.2 °C warmer than normal (1991-2020) [1], contributing to extreme fire weather and wildfire escalation. Fire season, defined by the Government of Canada as "the annual period during which forest fires are likely to start, spread, and cause damage" [9], is increasing in length [13] - over a 43 year period from 1961-2003, fire season in Alberta increased by a total of 51 days [14]; in western Canada, both the area burned and number of large fires have been trending upward since 1959 [13]. Additionally, large fires are growing larger: the fire size in the 95th percentile was approximately 57% greater in 2015 than in 1959 [13]. 2023 was an extreme example of what many have predicted: the increasing frequency and severity of wildfires in Canada attributed to anthropogenic climate change [15, 12, 8, 13]. By the end of this century, climate scenario projections conducted by Flannigan et al. [15] show a doubling of the area burned by wildfires in Canada.

Alberta's renewable energy transition, which aims to have 30% renewable energy by 2030 [16], could be undermined by the increasing impact of wildfires. Wildfire smoke reduces solar irradiation by scattering and absorbing sunlight [17, 5], directly affecting the amount of power that can be produced through solar generation. In 2023, Alberta represented 92% of Canada's growth in renewable energy and energy storage capacity [18], with some of the highest solar resource potential in the country (Figure 1). However, as wildfires intensify due to climate change, the increasing frequency and severity of smoke events may reduce Alberta's solar potential, inhibiting its decarbonization efforts. This could also reduce current solar power generation, causing grid instability and financial losses. This study aims to quantify and evaluate the effects of wildfire smoke on solar energy generation in Alberta.

2.1 Related works

The performance of solar photovoltaic (PV) power generation is determined by various factors, including system technology, equipment choice, and environmental conditions, with solar irradiance (GHI) the main input for solar power [20]. Temperature is a critical factor: higher temperatures generally reduce system efficiency [20]. Atmospheric conditions, such as dust, particulate matter $PM_{2.5}$, humidity, and wind speed, also significantly affect PV performance [20, 21]. Dust deposition can block sunlight and degrade the quality of solar cells, making a dust-free surface essential for optimal efficiency [20, 21]. Mekhilif et al. found that elevated humidity reduces PV performance, while wind speed can both reduce humidity and increase dust deposition [21].

With the intensification of wildfires in recent years, wildfire smoke has emerged as a potential factor affecting solar power generation. $PM_{2.5}$ is a commonly used indicator to assess the concentration of smoke in the atmosphere [7]. The atmospheric effects of wildfire smoke, particularly its interaction with solar irradiation, remain under study. Sokolik et al. observed that smoke can scatter or absorb solar radiation depending on conditions [5].

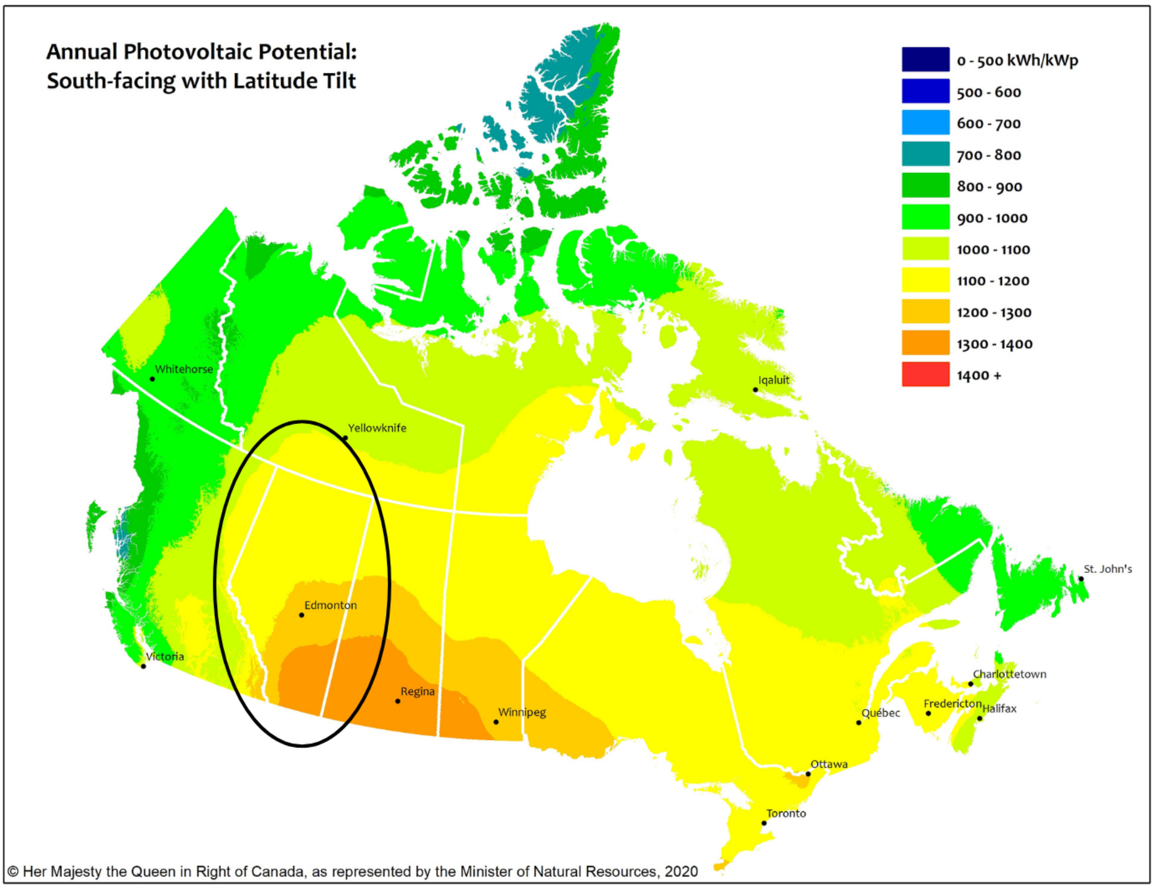

Figure 1: Annual photovoltaic potentials: south facing with latitude tilt (source: Government of Canada [19]).

Smoke can also penetrate PV cells, damaging semiconductors and reducing panel efficiency by scattering sunlight [22].

Studies in the United States highlight these effects: during severe wildfires in September 2020, California solar power production dropped by 13.4% compared to the previous year, despite increased system capacity [23], with reductions of 10–30% during peak hours [24]. A 2018 study of 53 sites in the Western U.S. found an average 8.3% reduction in solar output on smoky days [25], while another observed sunlight (GHI) reductions of up to 20% in the region [26]. Long-term trends indicate a 3.5% reduction in PV production in US regions such as the northern Rocky Mountains, near Alberta [27]. In New England, smoke from Canadian wildfires caused a 40% drop in solar energy generation after Canadian wildfires in 2023 [28].

Other international studies corroborate these findings. In Australia, wildfire smoke reduced solar production by 7% on average during the study period, with hourly peaks of 27% reduction [29], and another study showed hourly reductions of 20% to 65% [30]. In Spain, smoke caused daily reductions of up to 43% [31]. In West Africa, dust aerosols led to solar generation decreases of 13% [32], while in Kuwait, GHI on smoky days ranged between 70–87% of clear-day values [33]. Pollution-related particulate matter, assessed with the same indicators as wildfire smoke, exhibits similar impacts in Asia [34, 35, 36, 37].

As solar PV generation grows, planning for the impact of wildfire smoke becomes crucial. The reduction in output from wildfire smoke, is exacerbated by the "wiggle effect" - rapid fluctuations in PV output caused by particulate matter [38]. These fluctuations can destabilize the power grid. With increased use of solar energy, grid stability becomes more vulnerable, as solar power fluctuates more than traditional power plants, which provide more consistent output [38, 39]. Incorporating aerosol conditions into solar power forecasts can improve grid forecasting accuracy, and therefore grid stability, as shown by [40], who found improvement in 65% of stations when including Saharan dust into German PV forecasts. Additionally, machine learning models combining historical power data with meteorological parameters (e.g., temperature, solar irradiance, humidity, wind speed, cloud cover) have been shown to improve forecasting accuracy [41, 42].

The rising frequency and severity of wildfires underscores the importance of understanding how wildfire smoke affects solar power generation. Studies consistently show that smoke, through particulate matter and aerosols, reduces solar output and can destabilize the power grid due to fluctuations in power generation. Further understanding of the extent of these effects will be vital to adapt to future challenges and ensure reliable grid operation. With Alberta's focus on renewable energy integration and its considerable solar potential, this challenge becomes increasingly significant.

2.2 Research objectives and novel contributions

The effects of wildfire smoke and atmospheric aerosols on solar PV power generation have been studied in regions such as Asia and the United States, but it is essential to expand this research to regions with diverse climates experiencing significant solar PV growth. Alberta provides an ideal case study, given its rapid adoption of solar PV generation and wildfire smoke as the primary source of air pollution. Despite its relevance, a comprehensive evaluation of these effects in Alberta, or in Canada more broadly, has not yet been conducted.

This research uses a larger dataset compared to most previous studies, capturing the variability in smoke intensity and duration across multiple wildfire seasons. While a dynamic study has not been conducted, a broader temporal scope allows for insights into the long-term effects of repeated wildfire events on solar energy production. Additionally, this study examines a range of solar power sites, those that are operational, under construction, and proposed, providing a comprehensive analysis of how wildfire smoke affects Alberta's solar energy potential. Including both existing and future solar projects offers valuable insights into the long-term viability of solar power in the province, helping to identify potential risks to both current and planned investments in solar infrastructure. This scope will allow for a more nuanced understanding of how wildfire smoke could shape Alberta's renewable energy landscape. It will also offer valuable insights into the impact of wildfire smoke on PV production more broadly, serving as a reference for future studies in other regions.

One of the major contributions of this research is the estimation of potential financial losses of reduced solar power generation due to wildfire smoke. It will provide stakeholders - such as policymakers, utility companies, and investors - with data on the economic costs of these disruptions, supporting decision making regarding the feasibility of large-scale solar PV plants in regions at high risk of wildfire smoke.

Namely, Alberta's potential for diverse renewable energy sources, particularly wind power, offers an opportunity to reassess the province's renewable energy strategy in light of our study. Should significant vulnerabilities in solar power be identified due to wildfire smoke, policymakers may consider prioritizing complementary technologies that are less impacted by atmospheric pollution, thereby boosting Alberta's energy resilience during smoke events.

This research contributes to the ongoing discussions on climate change adaptation, with a particular focus on renewable energy systems. As climate change amplifies the frequency and intensity of wildfires, understanding these effects is crucial for building reliable energy infrastructure. The need to integrate real-time smoke data into solar PV forecasting models, to better manage grid operations and reduce the risk of energy shortages during smoke events, is highlighted. Ultimately, this study aims to inform renewable energy policies in Alberta and Canada, while enhancing academic understanding of climate-specific challenges to renewable energy.

3 Data and Methods

This section introduces datasets and methodologies used in this study, building on the recent approach presented by Gilletly et al. [25].

3.1 Datasets

Except for the Innisfail production dataset, all data was sourced from publicly available resources. The study spans from 2018 to 2023, specifically chosen to encompass recent wildfire trends in Western Canada, including record-breaking years (2018, 2021, 2023) and relatively mild years such as 2020 [43]. Data preparation and integration was performed in Python using an assortment of packages [44, 45, 46, 47, 48, 49, 50, 51, 52].

3.1.1 Station Selection

In this study $PM_{2.5}$ is used as a proxy for wildfire smoke, consistent with established research practices, as described in the previous sections. $PM_{2.5}$ is monitored by the Government of Alberta as part of the Canadian Ambient Air Quality Standards (CAAQS). A dataset detailing the geographic coordinates and monitoring periods of $PM_{2.5}$ was downloaded from the Alberta Air Data Warehouse [53]. Solar site candidates were identified using the Alberta Major Projects database, containing infrastructure projects with budgets exceeding $5 million Canadian dollars [54]. At the time of download, there were 41 $PM_{2.5}$ station candidates and 91 solar site candidates.

Geographical cross-referencing determined the inclusion of sites in the study. Solar sites within a 50 km radius of a $PM_{2.5}$ sensor were included and $PM_{2.5}$ monitoring stations closest to these solar sites were selected. A 50 km radius ensures reasonably accurate values at solar sites and is consistent with the similar studies [25]. One $PM_{2.5}$ station, Red Deer Riverside, was removed due to large amounts of missing data and its proximity, 9.4 km, to another station that could provide data for the same region. This process identified 28 solar sites and 12 $PM_{2.5}$ stations, with an average distance of 23.87 km between pairs. Most solar sites are in Southern Alberta, reflecting its high solar potential, with a gap in Southeastern Alberta due to a lack of nearby $PM_{2.5}$ stations that met the necessary criteria. See Figure 2 for the site map.

3.1.2 Particulate Matter $PM_{2.5}$ Data

Hourly $PM_{2.5}$ ($\mu g/m^3$) data was obtained from the Alberta Air Quality Data Warehouse for all stations included in the study [55]. Only "Good Quality" data, without flagged invalid entries, was downloaded, eliminating the need for outlier treatment [55]. Data preparation involved addressing duplicates and missing values. In cases where multiple $PM_{2.5}$ values existed for a given hour, the average was calculated. Each station had a number of missing values, which were filled using a weighted average method, with nearby stations assigned higher weights based on their proximity. This method relied on the synchronized trend in $PM_{2.5}$ between stations, demonstrated in Figure 3, to contextually fill the missing values.

3.1.3 Solar Generation Data

Due to the unavailability of historical production data, solar PV power generation was simulated at all 28 sites, differing from Gilletly et al.'s [25] methodology. The use of simulated

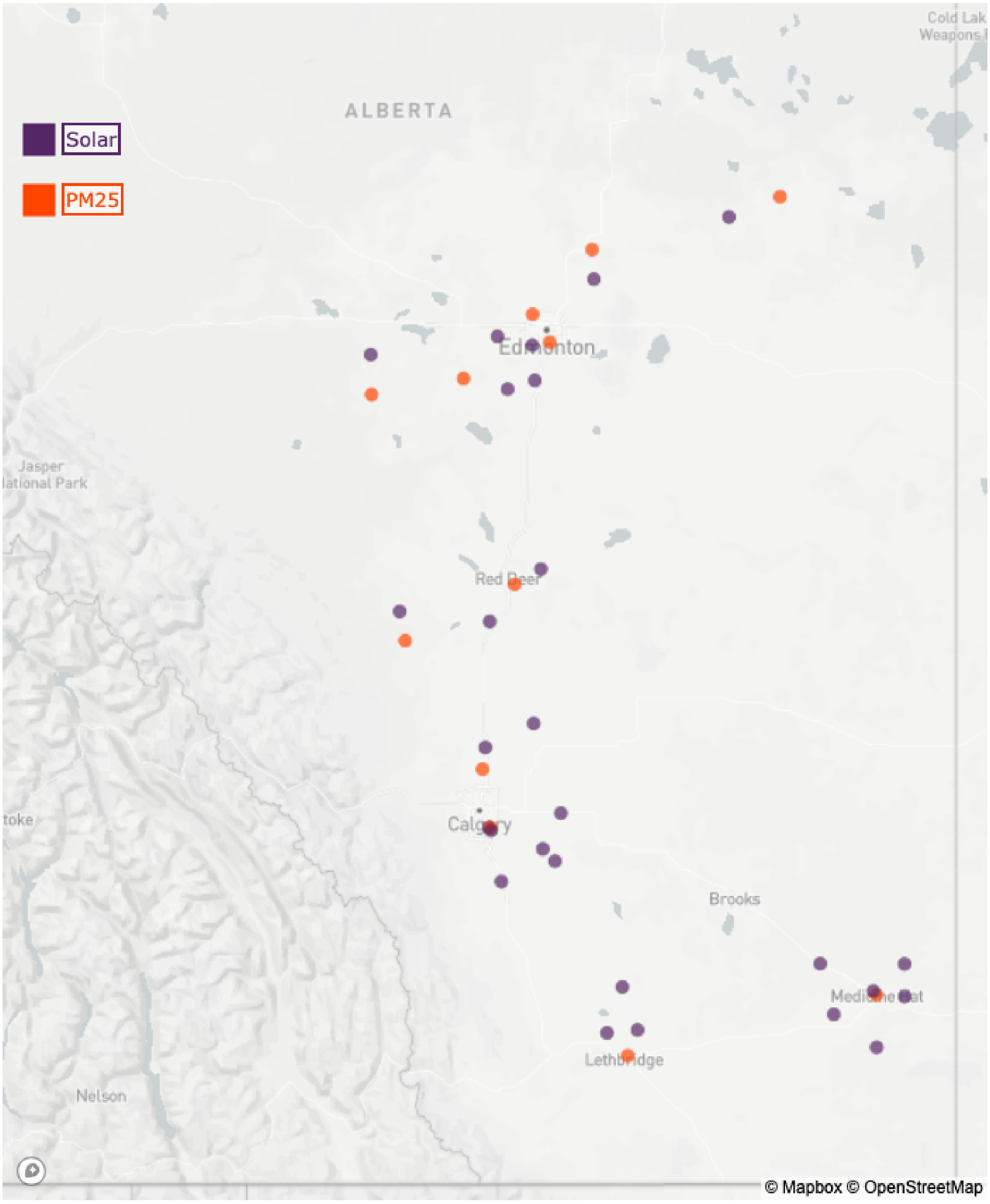

Figure 2: Map of solar PV stations & $PM_{2.5}$ monitoring stations.

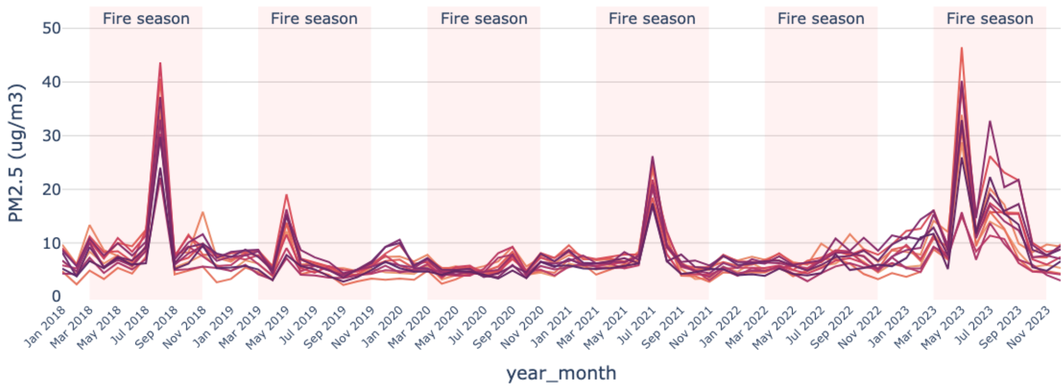

Figure 3: Monthly average $PM_{2.5}$ at each monitoring station.

data is a recognized approach in the literature [32, 17] and offers several advantages, including a larger dataset that incorporates sites under construction or in the proposal phase, and reduced data preparation requirements, as real-world data often includes downtime and recording errors.

The simulation used the publicly available System Advisory Model (SAM) software, specifically the PVWatts Model, which required environmental (weather) parameters and system design data for each site [56]. Weather data, pre-formatted for SAM, was obtained from the National Aeronautics and Space Administration (NASA) Langley Research Center (LaRC) Prediction of Worldwide Energy Resources (POWER) Project, using the Hourly API which provides pre-formatted satellite data for the renewable energy sector [57]. The data corresponds to the nearest satellite grid cell for each site. System design inputs, summarized in Table A.1. in the Appendix A, were gathered manually from the Alberta Utilities Commission application portal [58]. After assembling the necessary inputs, hourly solar production in kW was simulated.

To evaluate the precision of SAM's simulations, actual production data for the Innisfail site, provided by Elemental Energy, were used, spanning from July 2020 to December 2023 [59]. As seen in Figure 4, the simulation aligns reasonably well with the data observed during the fire season (March 1 to October 31) [60]. Despite the larger differences outside this period, the data remains reliable for drawing conclusions during the fire season. Possible reasons for production differences include site downtime, imperfect satellite weather observations or snow on solar panels.

3.1.4 Electricity Price Data

To estimate the financial impact of solar PV power generation losses due to smoke, monthly average pool price data from AESO (Alberta Energy Systems Operator), was converted from

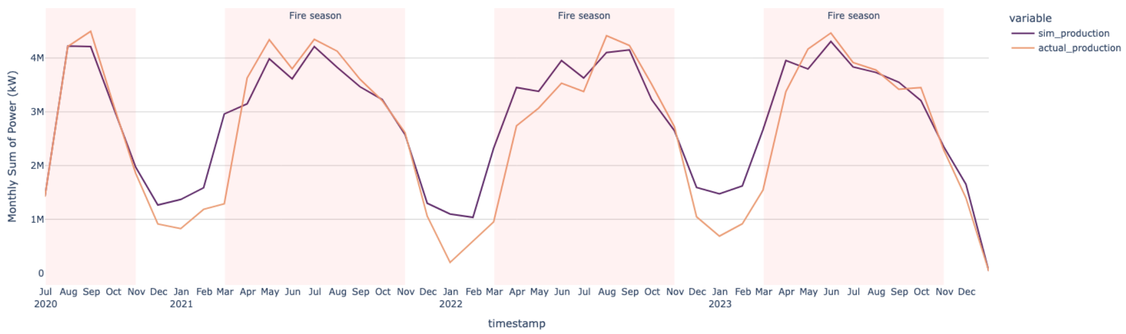

Figure 4: Comparison of actual and simulated production at Innisfail solar site [59].

Canadian dollars per MWh to cents per kWh, to match the hourly format of the dataset [61]. The pool price indicates the average price at which electricity is bought and sold on the market [62]. This data was then adjusted for inflation to December 2023 Canadian dollars using the National Power Selling Price Index from Statistics Canada [63]. The adjusted data will be used to calculate the monetary losses from reduced solar power production during wildfire smoke events.

3.1.5 Final dataset aggregation

$PM_{2.5}$ and SAM simulated production data were merged by matching each solar station production entry with the corresponding $PM_{2.5}$ value of the nearest station at the same time stamp. A separate download of hourly weather data, including parameters selected for the model - GHI, temperature, humidity, wind speed, and precipitation - was obtained from POWER Project via the Hourly API [57]. These parameters aligned with those used by Gilletly et al. [25], with the addition of humidity as an additional predictive variable [21]. The clearness index was initially considered but excluded on the recommendation of Gilletly et al. [25], and attempts to use Aerosol Optical Depth (AOD) were also abandoned due to data quality issues.

Before integration, the weather data was adjusted to the appropriate time zone, and data from February 29 were excluded from leap years, as the SAM simulation does not provide values for this date. Weather data was then combined with $PM_{2.5}$ and production datasets. The resulting dataset contained 1,471,652 hourly data points. Figure 5 demonstrates the data aggregation process.

A total of 39,983 (2.7%) rows were removed due to missing power generation despite non-zero GHI values, suggesting potential simulation anomalies, leaving 1,434,669 hourly data points for final analysis. To account for differences in equipment and production capacities between sites, Min-Max normalization [25] was applied, scaling each site's production between 0 and 1 relative to its maximum observed output during the analysis period. This normalization ensured comparability between sites.

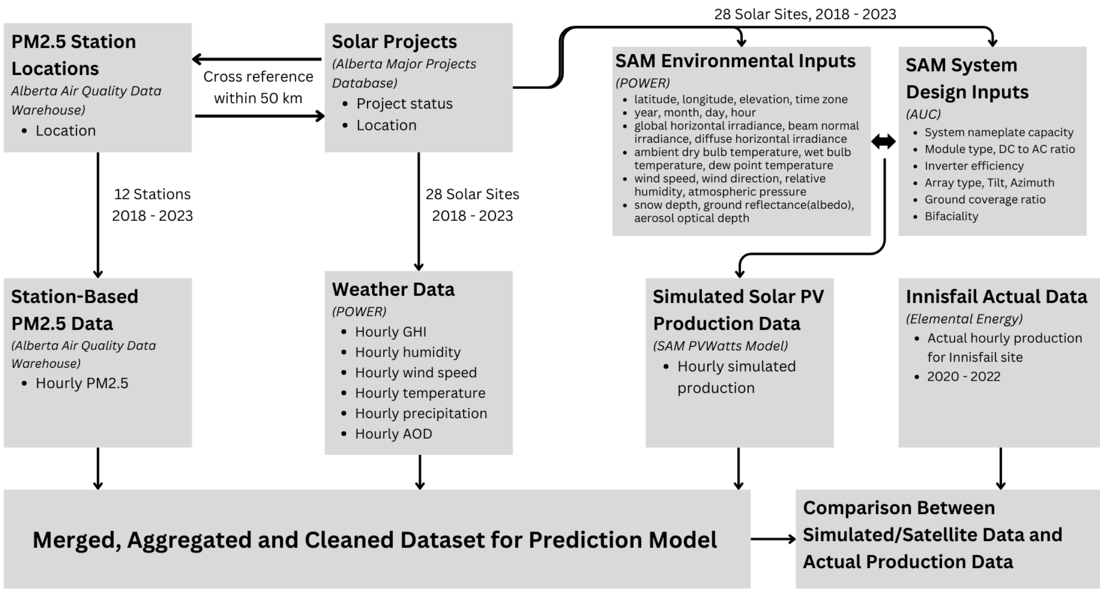

Figure 5: Data aggregation process.

3.2 The predictive model

We selected and developed a predictive machine learning model to forecast solar PV power production in Alberta, using it to isolate the impact of smoke on model predictions. Python was used for implementation, utilizing previously listed packages.

3.2.1 Model Selection

The literature highlights a strong preference for artificial intelligence methods in solar forecasting [64], with ensemble techniques, such as Random Forest Regression (RFR), emerging as a robust solution able to capture complex relationships in the data [65]. Chahboun et al. [66] found RFR superior to Multiple Linear Regression (MLR) and Support Vector Regression (SVR), while Torres-Barran et al. [67] emphasized the effectiveness of gradient-based ensemble methods like XGBoost. Das et al. [68] reviewed PV power prediction models, noting that while Artificial Neural Networks (ANNs) and Support Vector Machines (SVMs) perform well, ANN's high computational cost and risk of overfitting warrant caution. In some instances, RFR has outperformed ANNs in solar PV power prediction [41]. Hence, RFR, SVR and XGB are considered in our model selection process.

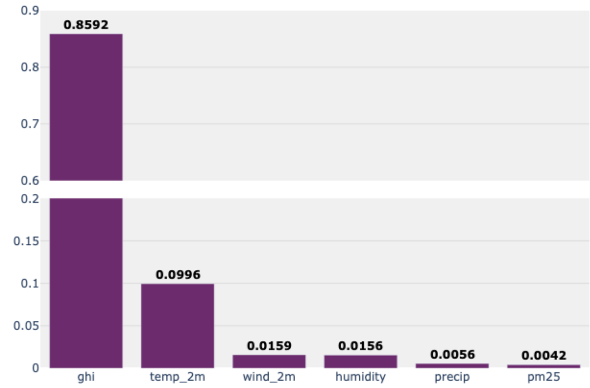

Figure 6: Model feature importance.

3.2.2 Model Training

In initial model training, the first $\approx 83\%$ of the dataset (2018-2022) was used for training, with the remaining 17% (2023) reserved for testing. This time-based split ensures balanced training data and prevents potential bias that could arise from only including a portion of the year in model training. The performance of the model was evaluated using Root Mean Squared Error (RMSE) and the coefficient of determination (R^2), offering an understanding of predictive accuracy and ability to capture variance.

The baseline models for RFR, SVR, and XGB were compared. SVR was excluded due to impractical training speeds for large datasets, as Scikit-learn's SVR is designed for datasets up to 10,000 rows [50]. Among the remaining methods, RFR and XGB performed comparably, and we chose to use RFR for its established effectiveness and basis in similar studies [25]. RFR produced reliable predictions, aligning well with the objectives of this study, with our emphasis on application rather than model innovation.

Randomized Search Cross Validation [50] was employed for RFR hyperparameter optimization, sampling from a defined search space to reduce computational costs. Search spaces were adapted from Torres-Barran et al. [69] from similar optimization tasks, with the best results used to finalize the model parameters. The model's ability to generalize to unseen locations was evaluated using a leave-one-group-out strategy at the site level, as described by [25]. In each iteration, one site was excluded as the test set, while the remaining sites were used for training, assessing predictive accuracy to determine how well the model would adapt to new sites not seen in the training process. This process was repeated for all 28 sites, resulting in an average RMSE of 0.0764 and an average R^2 of 0.9421, indicating that the model generalized well to new location data.

Following a satisfactory assessment of the model's predictive accuracy, the model was trained on the full dataset. The feature importance, as depicted in Figure 6, highlights the contribution of the individual variables.

3.3 Isolating Wildfire Smoke Impacts

To assess the impact of wildfire smoke on solar PV power production, the original dataset was filtered for periods with high observed $PM_{2.5}$ levels, corresponding to the red (severe: $PM_{2.5} > 27$) and orange (moderate: $PM_{2.5} \geqslant 20$) thresholds in the Canadian Ambient Air Quality Standards [70], and positive GHI values, indicating theoretical production hours. The model was used to predict power generation during these smoky periods. Subsequently, the monthly mean $PM_{2.5}$ value under "clear" conditions ($PM_{2.5} \leqslant 10$) was calculated, and high observed $PM_{2.5}$ values in the smoke dataset were replaced with this clear monthly value, creating a synthetic dataset without smoke. Predictions were then made on the synthetic dataset, holding all other factors constant, to isolate the effect of $PM_{2.5}$ on predicted power output.

This analysis also extends to the evaluation of the financial implications of wildfire smoke on solar PV production within Alberta's deregulated electricity market. In this market, electricity is traded based on the pool price, which represents the cost per megawatt-hour paid to generators, as previously described [62]. Although some producers operate under private power purchase agreements, this study assumes that all solar PV producers sell at the pool price to estimate financial losses. Monthly average hourly pool prices, adjusted for inflation to December 2023 values, were multiplied by the predicted hourly power losses and aggregated over the analysis period to quantify financial impacts in Canadian dollars.

4 Results and discussion

4.1 Exploratory Analysis

Figure 7 displays weekly average levels of $PM_{2.5}$ across monitoring stations during the study period, highlighting significant increases during fire season. The most severe levels were observed in 2023, 2018 and 2021, with occasional peaks in 2019. In particular, weekly average values of $PM_{2.5}$ in Alberta exceeded levels of orange and red exclusively during the fire season, highlighting wildfire smoke as the main source of severe $PM_{2.5}$ pollution in the province. Among the study years, 2023 exhibited the highest sustained smoke levels throughout the province, with an average $PM_{2.5}$ concentration of 13.93 $\mu g/m^3$ during the fire season. 2021 and 2018 also had notable concentrations of $PM_{2.5}$, with the 2020 fire season having the lowest concentration at 4.96 $\mu g/m^3$.

An analysis of simulated solar generation data reveals that days characterized by elevated $PM_{2.5}$ levels rarely reach the high end of the production spectrum, as illustrated in Figure 8. This indicates a negative correlation between high $PM_{2.5}$ levels and solar power production. Solar power generation exhibits a clear seasonal pattern, with higher output in the summer months, coinciding with the fire season. The alignment of smoke periods and peak production times presents potential challenges for solar power production in Alberta.

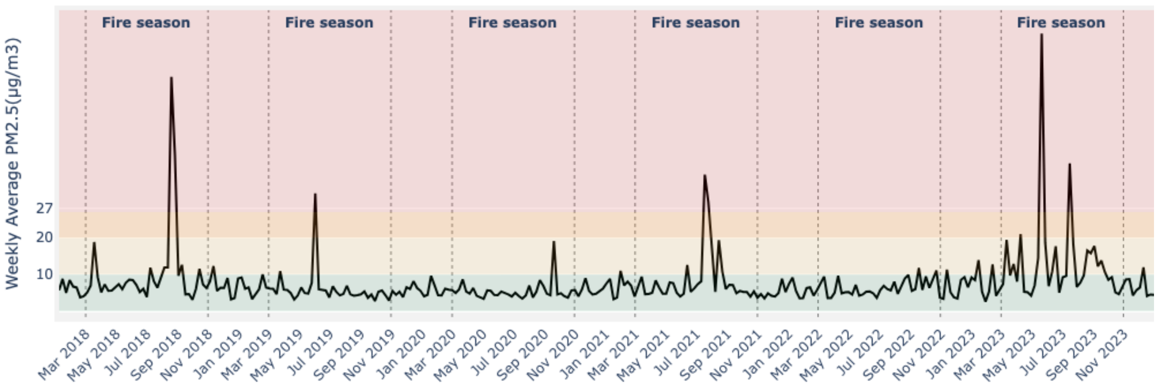

Figure 7: Weekly average $PM_{2.5}$ across all studied monitoring stations.

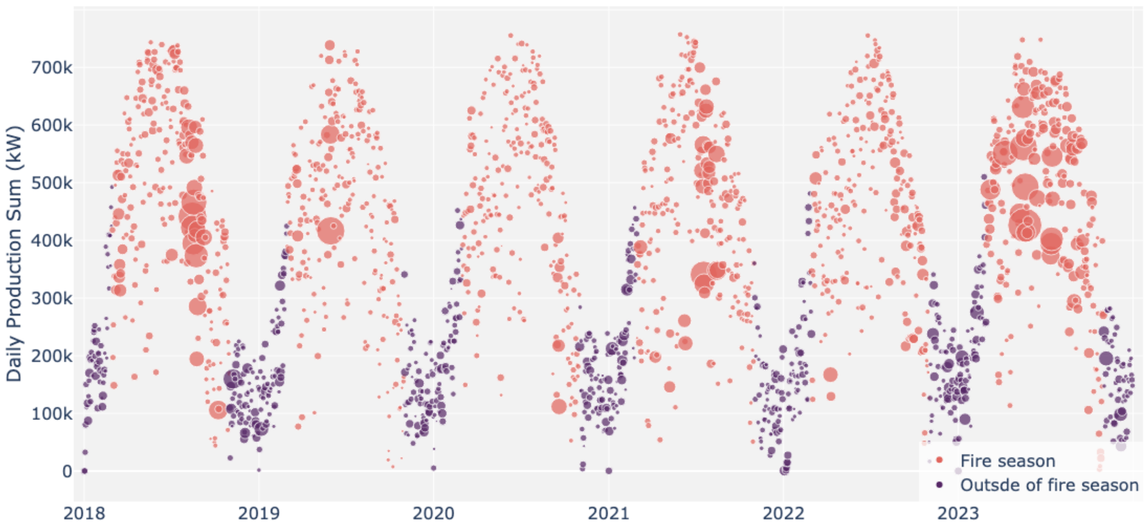

Figure 8: Daily sum of solar power produced (kW), sized by daily average $PM_{2.5}$.

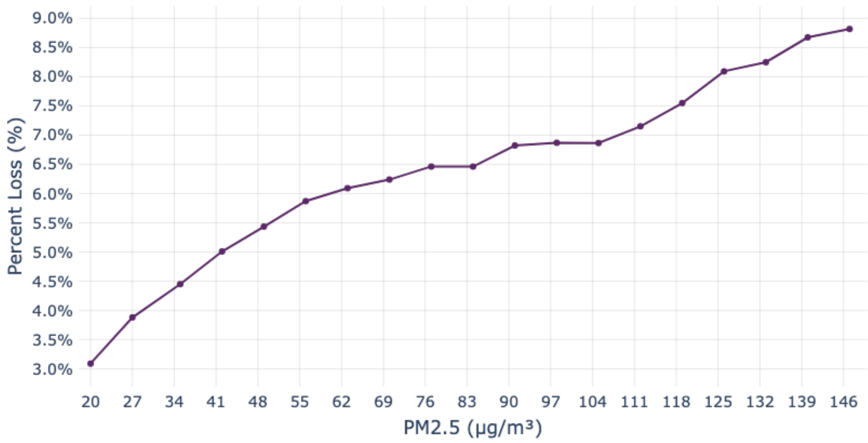

Figure 9: Percent losses at varying levels of $PM_{2.5}$.

4.2 Isolated wildfire impacts and financial implications

During periods of moderate to severe wildfire smoke over the duration of the study, ($PM_{2.5} \geqslant 20$), solar power generation in Alberta experienced a mean reduction of 3.09%, increasing to 3.91% under severe conditions ($PM_{2.5} > 27$). Throughout the six fire seasons, the cumulative impact led to a 0.19% average generation loss, equating to an estimated financial loss of \$4,514,160. Analyzing power losses at 7 µg/m³ $PM_{2.5}$ intervals ($n \geqslant 1500$; Figure 9) revealed a consistent trend: higher smoke levels corresponded to greater losses in production, in fact, severe smoke ($PM_{2.5} > 27$) accounted for 77.66% (\$3,505,751) of all financial losses in the study, demonstrated in a yearly breakdown seen in Figure 10. With consensus in the scientific community indicating a worsening Canadian fire regime, these power reductions are expected to escalate as severe smoke levels occur within the province more frequently, highlighting the growing economic and operational risks of worsening wildfire smoke.

Solar power losses were most pronounced in 2021 and 2023, with 2023 experiencing the highest total financial impact at \$1.8 million, due to higher electricity prices, despite greater MW losses in 2021 (Figure 10). The timing of wildfire smoke events seems to play a crucial role: in 2021, smoke was concentrated in July, when longer daylight hours and higher solar irradiance maximize PV generation potential. In contrast, 2023's smoke events occurred primarily in May, a period with less sunlight and higher precipitation potential (Figure 11). This seasonal difference likely explains why the largest monthly financial loss occurred in July 2021 (\$1.2 million), seen in Figure 12. In terms of relative power reductions over the fire season, 2021 saw the greatest impact (4.67%), followed by 2018 (3.69%). A summary of yearly results can be found in Table B.2. in the Appendix B. Further research on PV seasonality and its interaction with wildfire smoke could improve understanding of how the timing and duration of smoke events affect solar power production.

When examining production losses by location, we found that sites in Southern Alberta experienced greater impacts, as shown in Figure 13. These sites demonstrate larger reduc-

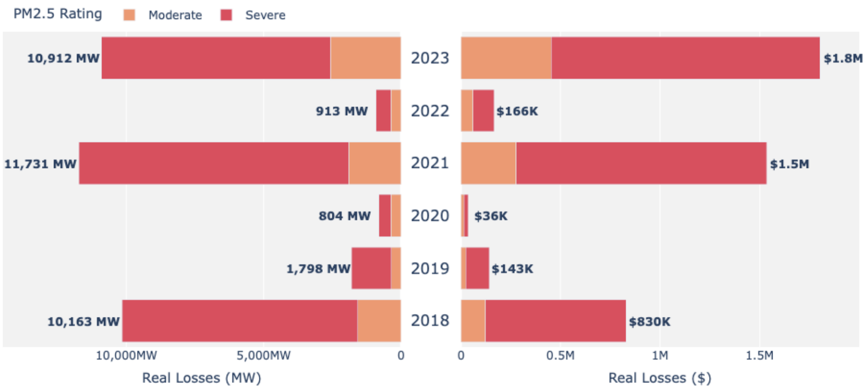

Figure 10: Yearly losses attributable to wildfire smoke by $PM_{2.5}$ rating.

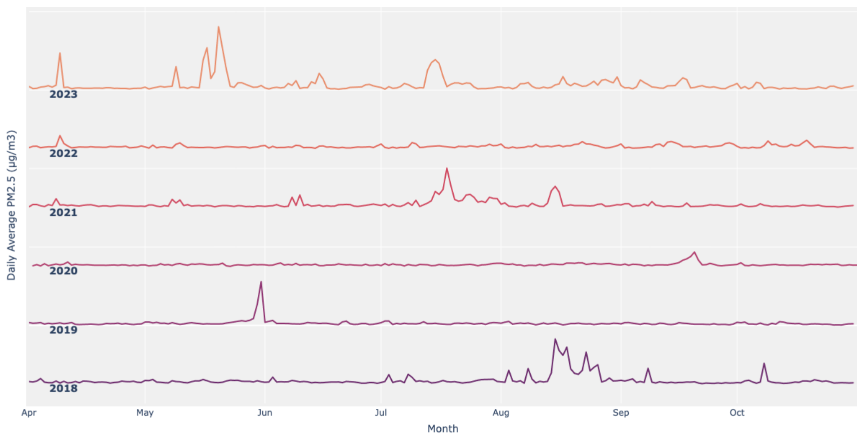

Figure 11: Daily average $PM_{2.5}$ levels by year.

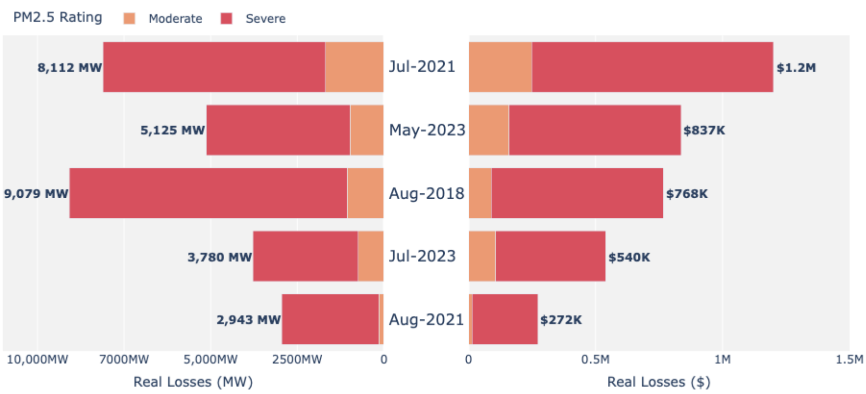

Figure 12: Largest monthly losses attributable to wildfire smoke by $PM_{2.5}$ rating.

tions in normalized production and financial losses. Possible explanations include elevated levels of smoke present in Southern Alberta during the study period, or the region's higher solar PV potential, which amplifies production losses.

Over the six-year study, wildfire smoke led to site-wide power losses ranging from 6.29% (Innisfail) to 1.13% (Sollair), as summarized in Table B.3 in Appendix B. Variations in normalized losses may be attributed to differences in smoke exposure, solar resource potential, panel technology, and localized atmospheric effects. Larger facilities experienced greater financial losses, with Georgetown (230 MW) exhibiting the most significant decline in both monetary terms and normalized power output. Figure 14 illustrates a dramatic production decline at Georgetown in May 2023 as $PM_{2.5}$ levels exceeded 300 µg/m^{3}. Georgetown is currently in the proposal stage. Given the observed effects, it may be wise to consider the potential impacts of smoke on this site and how they can be best mitigated.

Several stations highly susceptible to financial losses are in the proposal or construction stages (Figure 15), reflecting Alberta's growing large-scale solar capacity. Earlier projects were smaller, often pilot initiatives, while newer, larger facilities are more exposed to financial losses. As project size increases, so does the potential for revenue losses due to smoke-related power reductions. Future planning should account for these risks through improved forecasting, adaptive technologies, and site-specific mitigation strategies.

5 Conclusions

This study quantifies the impact of wildfire smoke on solar photovoltaic (PV) power generation in Alberta, revealing a consistent reduction in energy output during smoke events, aligning with findings from other regions. Given the intensifying wildfire regime driven by climate change and Alberta's growing reliance on renewable energy, these findings underscore the need to integrate wildfire-related risks into energy planning and policy.

From our results, moderate to severe wildfire smoke ($PM_{2.5} \geqslant 20$) resulted in average power reductions of 3.09% with total financial losses reaching approximately $4.5 million. The most severe impacts were observed during the 2018, 2021 and 2023 fire seasons - record setting years - where $PM_{2.5}$ spikes curtailed solar output. Severe smoke episodes ($PM_{2.5} > 27$) represented 77.7% of financial losses, with an average decline of 3.91%, underscoring their disproportionate impact. Losses consistently increased with the severity of smoke levels, highlighting the correlation between higher $PM_{2.5}$ concentrations and reduced solar production. As wildfire intensity and frequency continue to rise, policymakers and industry must address the risk of smoke disrupting solar energy in Alberta - even from fires thousands of kilometers away.

The finding that 2021 incurred the most significant losses in production, despite having lower average $PM_{2.5}$ levels than 2023, suggests that the timing of smoke events, alongside seasonal and daily variations, plays a critical role in solar PV reductions due to wildfire smoke. While this study focuses on the general relationship between wildfire smoke, PV production losses, and financial losses, the temporal-spatial dependencies of smoke events warrant further investigation. The timing of smoke events could be as impactful as smoke

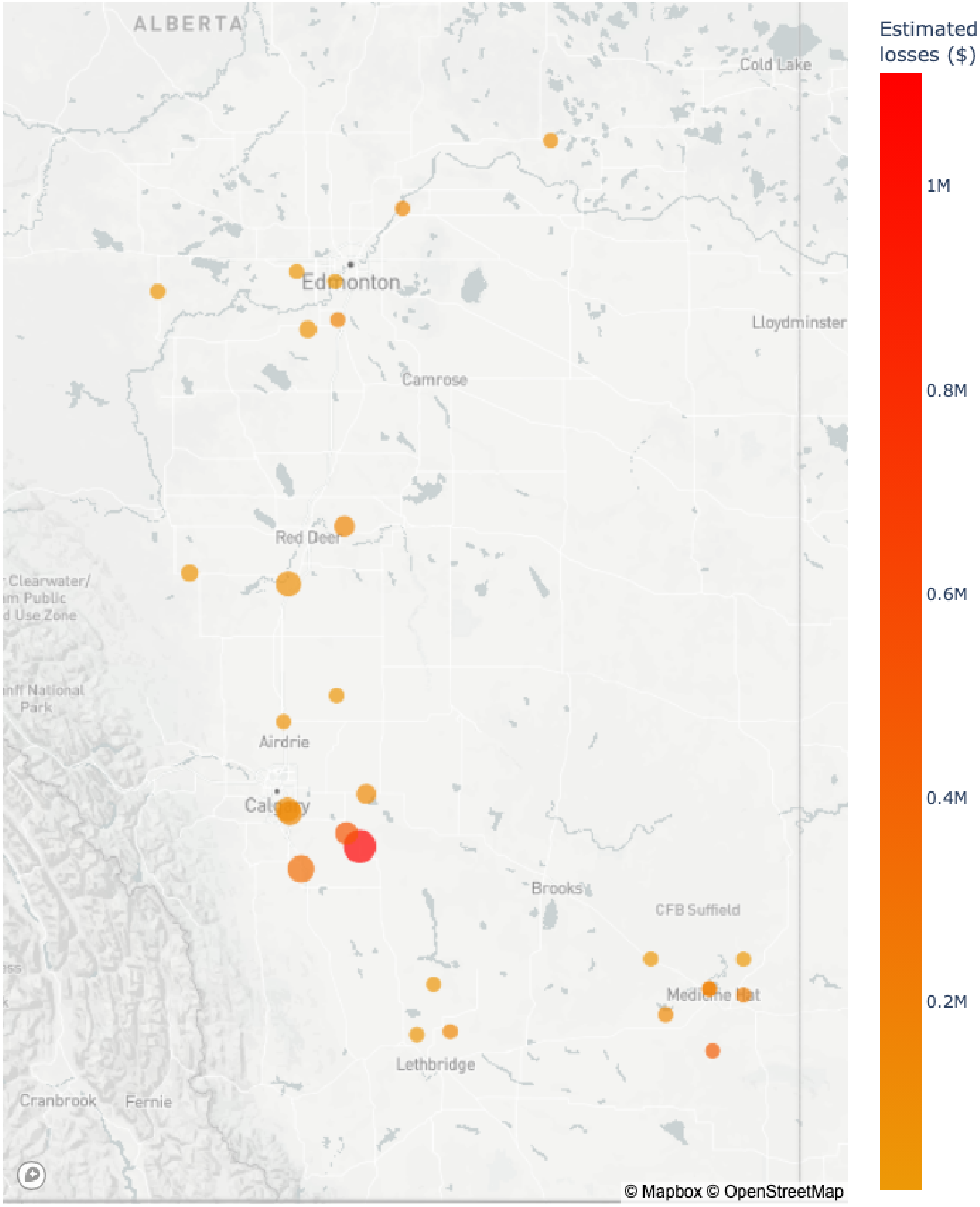

Figure 13: Differences in solar power production, sized by normalized losses, coloured by financial losses.

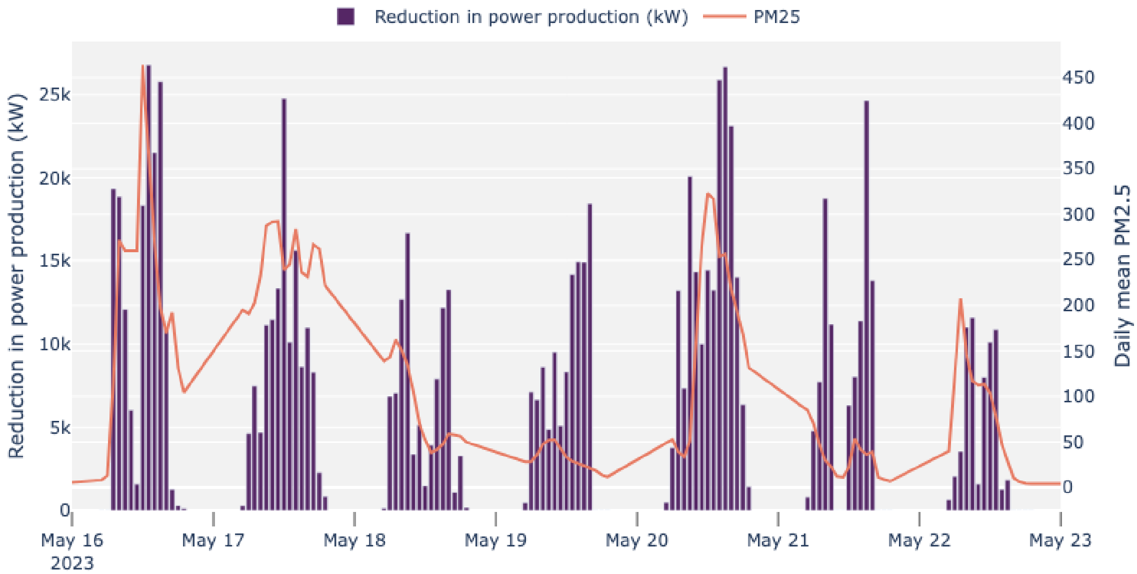

Figure 14: Reduction in solar power production at Georgetown in May 2023.

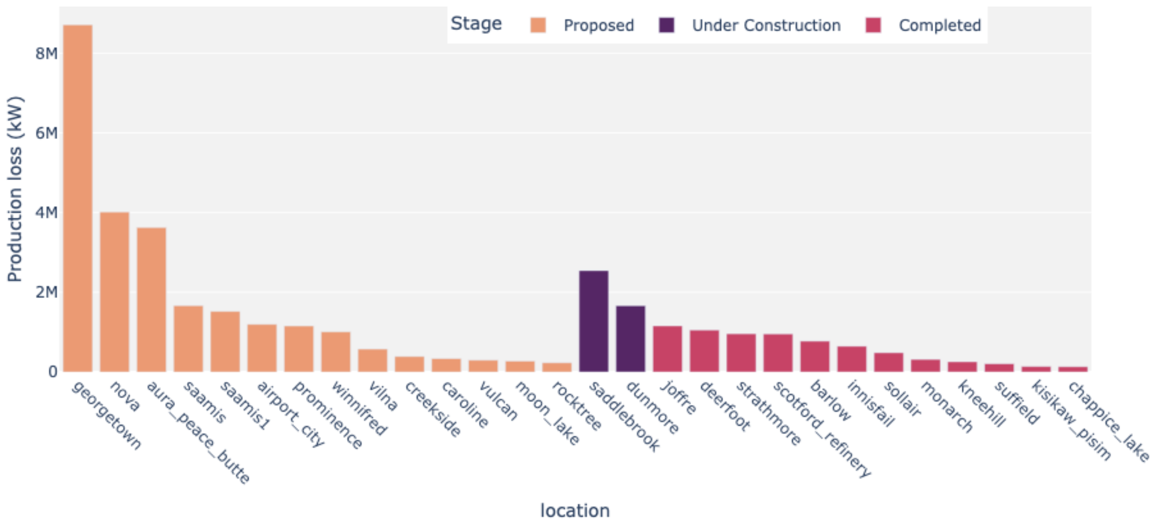

Figure 15: Total production loss attributable to smoke, by project stage.

intensity in driving solar PV losses. The alignment between fire season and peak solar production periods further complicates energy planning and grid stability, highlighting the need to better understand how smoke and additional environmental factors interact to influence solar PV performance.

Although normalized solar PV production losses were consistent across most stations, the pronounced impact in Southern Alberta suggests regional sensitivity to smoke, calling for further investigation into atmospheric patterns and transport mechanisms. Significant losses at larger production sites and those under construction reveal the vulnerability of major solar facilities to wildfire smoke, underscoring the urgency of developing strategies to bolster grid stability and strengthen the resilience of key infrastructure for consistent power generation province-wide.

Given that this study encompasses completed, proposed and under construction projects, its purpose lies in assessing the possible impact of smoke on Alberta's solar PV power potential, rather than providing an evaluation of actual historical events. If the study had exclusively considered completed projects over the period studied, the effects in terms of power production losses in MW and financial implications would likely be different, as many of the largest contributing projects are not complete. Furthermore, several of Alberta's largest solar projects, including the Travers Solar site (465 MW), the largest in Canada, were excluded from this study due to their lack of proximity to a PM2.5 station that met the established criteria [71]. This omission will also affect results province-wide. Nonetheless, considering the overall similarities among sites in terms of normalized and percentage-wise production loss, the losses would likely be similar when compared in relative terms.

The use of satellite environmental data rather than onsite measurements, offsite $PM_{2.5}$ values, and simulated solar PV production data, will also have an impact on the precision of the results. However, given the comparative analysis conducted between the simulated and actual data for Innisfail, this is not a major concern. Additionally, this study does not consider the effects of particulate matter deposition on solar panels, which have also been shown to contribute to significant reductions in production [35]. This may lead to an underestimation of the reductions in solar PV power generation attributed to wildfire smoke demonstrated in our study.

Despite these limitations, this study provides a functional estimate of the potential impacts of wildfire smoke on solar power generation in Alberta. While further refinement and exploration are needed to address identified constraints, the presented findings serve as a critical starting point to understand the interaction between wildfire smoke events and solar energy production in the province, as well as contribute to the overall body of knowledge on how wildfire smoke affects solar PV power generation.

This study underscores the lasting effects of environmental disruptions on renewable energy. It calls for the development of comprehensive energy planning strategies that prioritize resilience, enabling solar PV systems and the provincial electricity grid to withstand future challenges and continue to thrive in an increasingly volatile climate.

6 Code and data availability

With the exception of actual Innisfail production data, provided by Elemental Energy, all data used in this study was obtained from public sources. The assembled data, random forest regression model and sample Python code used to obtain results will be made public upon publication.

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7 CRediT authorship contribution statement

Samantha M. Treacy: Conceptualization, Methodology, Software, Formal Analysis, Data Curation, Writing - Original Draft, Writing - Review & Editing, Visualization, Project Administration. **Alexandra B. Moura:** Writing - Original Draft, Writing - Review & Editing, Supervision, Project Administration

8 Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors utilized ChatGPT to improve readability and language. Following the use of this AI-assisted tool, the authors carefully reviewed and edited the content as necessary and assume full responsibility for the final version of the publication.

A System Advisory Model Simulation Requirements

Variable name	Description
System nameplate capacity, kWdc	The maximum rated electrical output capacity of the solar power system under standard test conditions, measured in kilowatts direct current (kWdc).
Module type	The categorization of solar panels into standard, premium, or thin-film modules, representing different technologies and efficiency levels.
DC to AC ratio	The ratio of the direct current (DC) power generated by the solar panels to the alternating current (AC) power delivered to the electrical grid.
Inverter efficiency	The efficiency of the inverter in converting DC power generated by the solar panels into usable AC power for the electrical grid.
Array type	The configuration of the solar panel array, including options such as fixed open rack, fixed roof mount, 1-axis tracking, 1-axis backtracking, and 2-axis.
Tilt, degrees	The angle at which the solar panels are tilted from the horizontal plane, measured in degrees, influencing exposure to sunlight and energy production.
Azimuth, degrees	The compass direction the solar panels face, measured in degrees, indicating the orientation of the panels towards the sun for optimal energy capture.
Ground coverage ratio (GCR)	The ratio of the total surface area covered by solar panels to the total ground area, influencing power density and land utilization. In some cases this information was not available, and a value of 0.3 is used, which is the default value in the software, and also that recommended by an industry expert.
Bifaciality	A binary variable indicating whether the solar panels are bifacial, capable of capturing sunlight from both the front and rear sides. Options include "Yes" or "No."
List of environmental inputs for SAM	latitude, longitude, time zone, elevation, year, month, day, hour, global horizontal irradiance, beam normal irradiance, diffuse horizontal irradiance, ambient dry bulb temperature, wet bulb temperature, dew point temperature, wind speed, wind direction, relative humidity, atmospheric pressure, snow depth, ground reflectance(albedo), and aerosol optical depth.

Table 1: Required system design inputs for SAM simulation. All descriptions sourced from SAM software documentation [56].

B Results Summary

Year	**2018**	**2019**	**2020**	**2021**	**2022**	**2023**	**Entire Study**
Average $PM_{2.5}$ (µg/m³)	10.23	5.86	4.96	8.55	5.93	13.93	**8.24**
Observations $PM_{2.5} \geqslant 20$	9,353	2,371	1,715	7,846	3,010	13,813	**38,108**
Observations $PM_{2.5} > 27$	6,482	1,250	748	5,510	1,319	8,857	**24,166**
Mean % production loss ($PM_{2.5} \geqslant 20$)	3.69%	2.69%	2.01%	4.67%	0.92%	2.47%	**3.09%**
Mean % production loss ($PM_{2.5} > 27$)	4.24%	4.30%	2.93%	5.45%	1.23%	3.08%	**3.91%**
Mean % production loss over fire season ($PM_{2.5} \geqslant 20$)	0.31%	0.06%	0.02%	0.37%	0.03%	0.33%	**0.19%**
Mean % production loss over fire season ($PM_{2.5} > 27$)	0.26%	0.05%	0.01%	0.31%	0.02%	0.26%	**0.15%**
Total power loss (MW) ($PM_{2.5} \geqslant 20$)	10,163	1,798	804	11,731	913	10,912	**36,320**
Total power loss (MW) ($PM_{2.5} > 27$)	8,442	1,422	388	9,646	517	8,327	**28,741**
Proportion of power losses ($PM_{2.5} > 27$)	83.06%	79.09%	48.21%	82.23%	56.58%	76.31%	**79.13%**
Hypothetical $ losses ($PM_{2.5} \geqslant 20$)	$829,559	$143,461	$35,816	$1,536,478	$166,003	$1,802,845	**$4,514,160**
Hypothetical $ losses ($PM_{2.5} > 27$)	$693,127	$116,133	$18,496	$1,233,991	$100,059	$1,343,943	**$3,505,751**
Proportion of hypothetical $ losses ($PM_{2.5} > 27$)	83.55%	80.95%	51.64%	80.31%	60.28%	74.55%	**77.66%**

Table 2: Impacts of wildfire smoke on solar energy production.

Location	**Stage**	**Mean % production loss**
Innisfail	Completed	6.29%
Joffre	Completed	5.19%
Georgetown	Proposed	4.99%
Saddlebrook	Under Construction	4.24%
Caroline	Proposed	4.09%
Vilna	Proposed	3.85%
Barlow	Completed	3.75%
Deerfoot	Completed	3.74%
Creekside	Proposed	3.64%
Nova	Proposed	3.58%
Winnifred	Proposed	3.55%
Aura Peace Butte	Proposed	3.35%
Strathmore	Completed	3.16%
Moon Lake	Proposed	2.54%
Prominence	Proposed	2.42%
Vulcan	Proposed	2.31%
Monarch	Completed	2.25%
Saamis	Proposed	2.13%
Scotford Refinery	Completed	2.07%
Dunmore	Under Construction	2.07%
Saamis1	Proposed	2.06%
Chappice Lake	Completed	2.06%
Rocktree	Proposed	2.03%
Suffield	Completed	1.93%
Kneehill	Completed	1.80%
Kisikaw Pisim	Completed	1.52%
Airport City	Proposed	1.41%
Sollair	Completed	1.13%

Table 3: Mean % production loss at site locations during moderate smoke conditions ($PM_{2.5} \geqslant 20$).

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