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Design of Optimal Wireless Sensor Networks for enhanced wildfire risk mitigation at wildland–human interfaces

Juan Luis Gómez-González[a,b], Effie Marcoulaki[b], Alexis Cantizano[a], Myrto Konstantinidou[b], Raquel Caro[c], Mario Castro[a]

[a] *Institute for Research in Technology, ICAI School of Engineering, Pontifical Comillas University, c/ Rey Francisco, 4, 28008, Madrid, Spain.*
[b] *System Reliability and Industrial Safety Laboratory, Institute of Nuclear & Radiological Sciences & Technology, Energy & Safety, National Centre for Scientific Research "Demokritos", 15310 Ag. Paraskevi, Attiki, Athens, 60037, Greece.*
[c] *University Institute of Studies on Migration (IUEM), Chair in Disasters Fundación AON España, c/ Rey Francisco, 4, 28008, Madrid, Spain.*

Critical infrastructure and fire-vulnerable facilities are often located in close proximity to wildland domains, including urban settlements, human activity areas, and industrial zones. Vulnerability is frequently assessed through physical analyses of the fire's direct effects on specific types of facilities (e.g. storage tanks). However, wildfire dynamics and behaviour in the extended wildland domain are often neglected, overlooking scenarios where distant ignitions from wildfires can trigger Natech events and the release of hazardous substances, e.g., from Seveso sites, potentially leading to domino effects. Proper consideration of wildfire dynamics is essential to determine the response times required to prevent disasters. This study considers Wireless Sensor Networks (WSNs), as early detection systems, and uses wildfire simulation datasets to obtain statistical insights into response times and optimize the sensor locations accordingly. The study considers a case study of a wildland-industrial interface in Spain, including time-to-failure data on storage tanks in immediate fire proximity. Results demonstrate that early wildfire detection systems significantly enhance risk awareness, underscoring the potential of optimized WSNs for mitigating wildfire risks at wildland-human interfaces.

Keywords: Wildfires, Natech, Wireless Sensor Network, Optimization, Time-to-failure, Storage tank, Response time

1. Introduction

Wildfires at human interfaces are an escalating risk. When facing the wildland-industrial interface, including critical infrastructures, wildfire threats represent a type of Natech disaster with the potential to trigger severe incidents or domino effects. Notable examples are the Alberta fires in Canada, which disrupted oil sand production (Khakzad, 2018) and the South Korea wildfires that destroyed a liquefied natural gas plant facility and threatened the operations of a nuclear power plant (Park et al., 2023).

While the threat to Wildland-Urban Interface (WUI) has long been studied, wildfire threats to industry are increasingly recognized as an emergent hazard (Planas et al., 2023). However, regulations such as the Seveso III Directive have not yet recognized wildfires as a significant risk factor (European Parliament and Council of the European Union, 2012). Factors including climate change, the increase of human interfaces through urbanization, and the significant presence of flammable substances are key drivers for increased vulnerability of industrial facilities (Schug et al., 2023).

Current public regulations consider buffer distances for Seveso plants (Ricci et al., 2024), and propose guidelines (Partners in Protection, 2003) to reduce risks from heat and flame impingement. The majority of existing research focuses on the time-to-failure of containers susceptible to BLEVE events, such as atmospheric and pressurized storage tanks, due to radiant heat and flame impingement (Wu et al., 2020; Landucci et al., 2009). These studies often assess the probability of exposure, leading to cascading failures within a site, where the failure of one container propagates to others (Ricci et al., 2021).

However, the broader wildfire landscape (ignition probability, fire behavior and wildfire dynamics) is often neglected, highlighting the insufficiency of such measures. Examples of research efforts to address this gap are the proposal of probabilistic frameworks coupling wildfire dynamics to flame impingement on atmospheric storage tanks (Khakzad, 2019), or the delimitation of Wildland-Industrial Interfaces (WII) (Planas et al., 2023).

The current work argues that Wireless Sensor Networks (WSNs) can provide a cost-effective early wildfire detection system, if they are properly adapted to the fire landscape surrounding a vulnerable critical infrastructure (Mohapatra and Trinh, 2022). Therefore, we follow a data-driven approach to optimize the sensor locations using simulated fire dynamics to detect wildfires as early as possible. The optimal sensor localization will be such to maximize the available time for response until a Seveso disaster becomes imminent, as well as to protect the surrounding wildland.

2. Methodology

This section describes the optimization framework to find the optimal sensor locations. Figure 1 illustrates the general methodology presented in the following subsections.

2.1. *Wildfire simulation data*

The first step is to use available geospatial data, a set of scenarios for the possible weather conditions, and the possible ignition locations, to generate a dataset of wildfire simulation data. The dataset comprises a set of raster files with various spatio-temporal features (e.g. fire arrival times, burnt areas, fire front, etc.) of a wildfire initiated at a given location, under given weather conditions. This spatio-temporal information can be used to evaluate the performance of a given WSN in detecting a wildfire. The performance could be quantified as, for instance, the time the WSN takes to detect a fire, or the burnt area at the time of detection, etc. (see Section 2.3). Section 3 provides more information on the various data and the wildfire simulator used here.

2.2. *WSN representation*

Assuming a set of possible (valid) sensor locations, G, each WSN is represented as a binary vector, S, indicating the presence or absence of a sensor at each candidate location. For instance, given a set G=$\{g_1,g_2,g_3,g_4,g_5\}$ of 5 known geographical coordinates, a WSN with sensors placed on locations g_2 and g_4 is represented as the binary vector S=$\{0,1,0,1,0\}$.

For this study, all pixels, except those depicting potential ignition locations and urban/industrial land use, are considered as valid sensor locations. To avoid finite-size effects, the space where sensors can be located extends beyond the ignition grid, enabling the identification of the fastest detection location for each fire regardless of the main spreading direction.

2.3. *Evaluation of the WSN performance*

The problem of finding the best WSN configuration is formulated as a bi-objective optimization problem, minimizing the number of sensors (or the WSN cost) while maximizing detection performance. This is directly linked to the wildfire characteristics that must be addressed to mitigate their impact (e.g. suppression and ecological costs, response time, burnt area, fire perimeter...). An early wildfire detection system requires detecting fires at the earliest development stage. Detection times are estimated using wildfire simulations. Nevertheless, minimizing detection times implies that slow-propagating fires may overestimate low-danger fires, while very fast, and thus dangerous, are neglected until the fire has burnt a large surface. The burnt areas correlate with fire severity and fire spread (Mattioli et al., 2022), representing a suitable performance metric for an early wildfire detection system.

The wireless sensors can usually detect combustion gases, smoke, temperature, noise, or any other feature related to fire. This work assumes that a sensor is triggered when fire propagates to pixels where sensors are present. For a given simulation scenario and a known instance of the WSN, the detection time will be the minimum of arrival times at the sensor locations.

In the present study, we formulate the per-

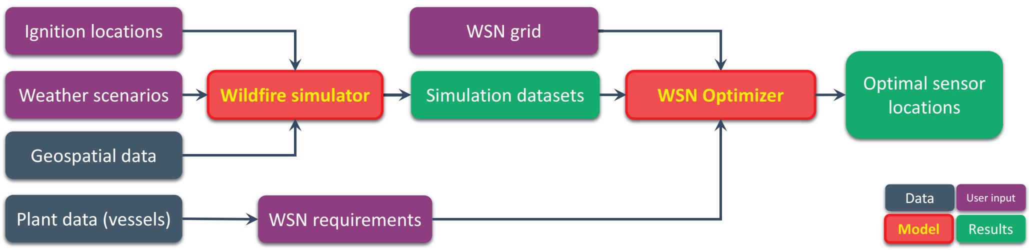

Fig. 1. Procedure for WSN design in cases of wildland areas surrounding industrial facilities

formance of any WSN instance as the weighted average of burnt areas at detection over all the wildfire scenarios. The contribution of each scenario to the weighted average depends on the frequency of weather conditions (based on historical weather data in the region) and the likelihood of the ignition location. Here, a uniform distribution is assumed for the ignition likelihood. The exact formulation of the objective function and the calculation of the weather frequencies are explained in (Gómez-González et al., 2025). The maximum allowable detection time can also be included as a problem constraint, based on the analysis of time-to-failure in Section 3.3. However, this is left for a future work.

2.4. *Optimization of WSN configuration*

In bi-objective optimization problems like the one considered here, the final solution is a set of non-dominated solutions approximating the Pareto front. In our case, the Pareto-front is a set of WSN configurations such that for each configuration, neither objective can be improved without detriment to the other (Skretas et al., 2022).

The sensor location problem is solved using evolutionary algorithms, particularly the Non-dominated Sorting Genetic Algorithm II (NSGA-II) (Blank and Deb, 2020). NSGA-II is a well-established optimizer available in the Pymoo Python library and has demonstrated efficiency in solving similar problems. More information on the optimization procedure can be found in (Gómez-González et al., 2025). Section 3 provides more details on the WSN representation and the optimization requirements.

3. Application case study

3.1. *Geospatial data*

For the case study, we use a well-studied WUI terrain and an extended dataset of wildfire simulations over different weather and ignition conditions. We consider a fictitious facility comprising atmospheric and pressurized tanks in the direct presence of wildland fuels. The domain is a raster representation of a real WII and WUI because the area includes a portion of the municipality of Cocentaina (Southeast Spain). The raster comprises 124 x 121 pixels, each covering 25 x 25 m^2, with a total surface of 937.75 ha.

3.2. *Wildfire simulations dataset*

This work uses a wildfire dynamic model validated in (Gómez-González et al., 2024). The set of wildfire simulations results from considering a grid of ignitions distributed over a regular grid, omitting urban and industrial land use, including 242 possible locations. Each scenario is simulated for up to 5 hours. To account for weather variability, each ignition is simulated under a series of meteorological conditions derived from the wind-rose (comprising 8 wind directions), constructed using historical wind data during days with high fire-weather indexes (FWI). Finally, the WSN optimizer is fed with a set of 1,936 simulations.

Figure 2-left illustrates the domain, highlighting the fuel cartography, the facility location, and the set of ignitions.

3.3. *Total response time in WII*

We can estimate the time available for response actions when a wildfire approaches a vulnerable

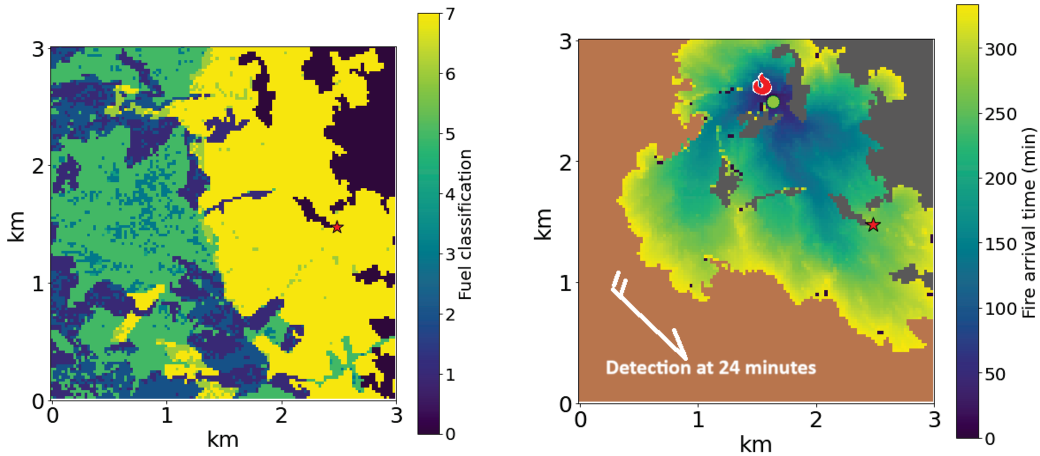

Fig. 2. **(Left)** Fuel type distribution in the fire domain and surface extension. ★ marks the storage tank. The fuel classification is encoded as; (0) Artificial, (1) Timber litter,(2) Southern rough, (3) Dormant brush, (4) Brush, (5) Chaparral, (6) Timber grass, (7) Short grass. **(Right)** A simulated wildfire spreads compromising the industrial facility. A sensor (noted ●) prompts a quick detection 24 min after ignition (noted by 🔥). The arrival time relative to the detection to the facility (noted ★) is 227 min.

site by analyzing (a) the fire detection times and (b) the total time available for response considering the location and type of industrial equipment that will be exposed to fire.

The total time available for response can be estimated using time-to-failure data for pressurized and atmospheric storage tanks present at the industrial facility. (Ricci et al., 2021), focused on four distinct types of vessels subjected to a variety of burning fuels at varying distances. They considered grass fuels around the industrial facility, so our case study is limited to this specific scenario. Figure 3 shows times-to-failure as a function of distance for different types and capacities of storage tanks.

Extrapolating the data from Figure 3 to our domain, flames can affect the industry across distances ranging from one pixel (for the 200 m^3 pressurized storage tank) to three pixels (for the 14,000 m^3 atmospheric tank) in the raster representation. The vertical red line in Figure 3 is the pixel resolution in our study. a50, a14000 represent atmospheric tanks with 50 m^3 and 14,000 m^3 volume capacity; p15, p200 represent pressurized tanks with 15 m^3 and 200 m^3 volume capacity, respectively. Data adapted from (Ricci et al., 2021). The time-to-failure for a given wildfire incident is determined by its minimum value of the burning fuel in the affected pixels. Our analysis computes the minimum available response time following detection, providing an approximate interval based on the worst-case scenario.

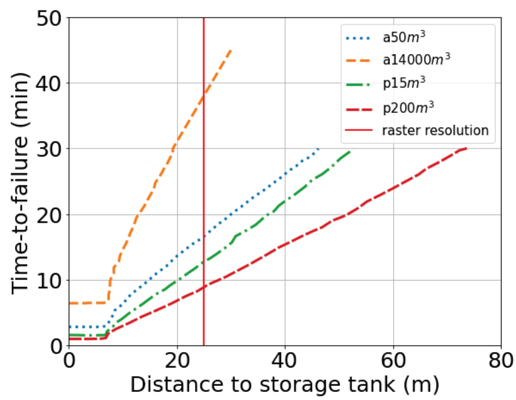

Fig. 3. Time-to-failure for storage tanks as a function of distance in case of grassfires.

Figure 2-right presents a simulated wildfire, characterized by the arrival times since ignition, leading to a Natech incident detected by a sensor.

4. Results

Figure 4 shows the set of final WSN configurations obtained using the optimization procedure outlined in section 2 for the case study.

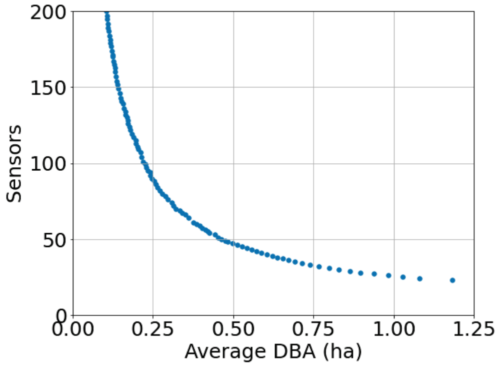

Fig. 4. Pareto optimal WSN configurations.

These results have been obtained using NSGA II with a population size of 100 individuals. The algorithm had a limit of 200,000 generations until achieving acceptable convergence over successive generations. For the sake of simplicity, we use the terms ”optimal” and ”Pareto front” for the set of final solutions. However, it is acknowledged that the final WSNs may be near-optimal and the final WSN population is an approximation of the actual Pareto front.

According to commercial sensor data, we need an average of 0.2 sensors per ha to cover a typical forest encompassing human interfaces (Dryad Networks GmbH, 2024). Since our study domain covers 937.75 ha, we require 188 sensors. Looking at our optimal WSNs, the configuration with the closest number of sensors is 189.

Figure 5 shows the locations of the sensors, either within the Natech region (grass) surrounding the Seveso site or the wildland.

Depending on wind conditions and the proximity of the ignition to the facility, a wildfire may or may not impact on it. In this scenario, 27% of fires can potentially trigger a Natech incident.

The capability of our WSN to enhance response times against a potential Natech incident lies in analyzing those sensors that detect that threat,

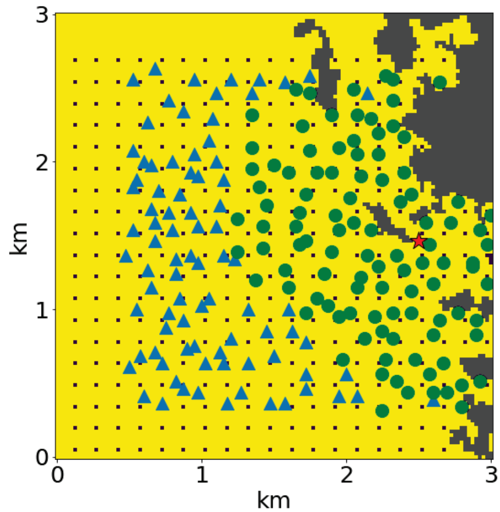

Fig. 5. Optimum WSN featuring 189 sensors. ▲ denote sensors located in the wildland, and ● sensors detecting potential Natech threats. ★ marks the storage tank. The gridded dots represent the ignitions.

along with the simulated time between detection and the fire’s arrival at the facility. Additionally, the available time-to-failure is assessed. Sensors triggering detections of fires potentially leading to a Natech incident are highlighted in Figure 5.

Based on the set of wildfires identified as potentially leading to a Natech incident, we calculate the response times as follows:

$$t_{\mathrm{R,i}} = t_{\mathrm{A,i}} - t_{\mathrm{D,i}} + min_{\mathrm{j}}(TTF_{\mathrm{j}}) \tag{1}$$

Where, $t_{R,i}$ is the minimum allowable response time for simulation i; $t_{A,i}$ is the arrival time for simulation i; TTF_j is the time-to-failure for equipment type j; $min_j(TTF_j)$ is the lowest TTF from the burning wildland fuels surrounding the facility (in this case TTF only depends on the fuel-to-tank distance); and $t_{D,i}$ is the detection time for simulation i.

Using Equation (1) over all the ignition locations and considering the meteorological conditions, we obtain a distribution of response times for each tank. Figure 6 presents the distributions for the four analyzed storage tank types.

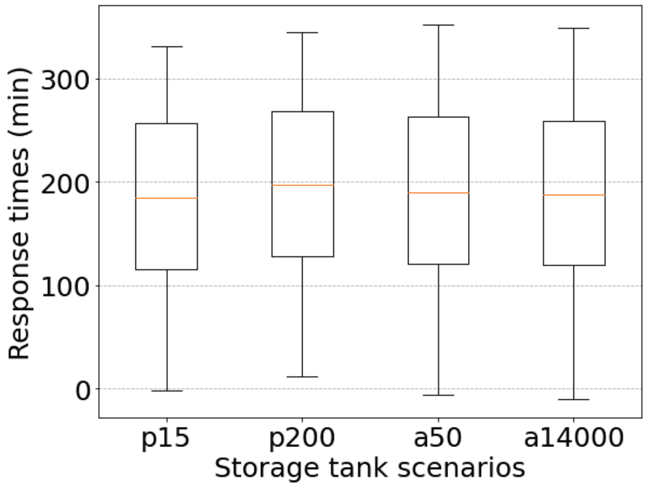

Fig. 6. Boxplots showing the response time distributions for wildfires threatening the four storage tank types analyzed in (Ricci et al., 2021).

5. Discussion

In the discussion we consider the optimal WSN comprising 189 sensors. It is reminded that in the present study the optimization does not consider the presence of the facility. The results from Figure 6 demonstrate that time-to-failure constitutes a small fraction of the available response times when an effective early wildfire detection system is implemented. Note that, according to state reports, in Spain, 80% of uncontrolled fire events are suppressed within 45 minutes after detection (Ministry for the Ecological Transition and the Demographic Challenge (MITECO), 2019).

Given the sensor coverage density in this study and the 1936 wildfire simulations we consider here, 95% of these fires are detected within one hour, with an average detection time of 26 minutes. Only 27% of all the wildfires are expected to threaten the facility. From these, 7% are causing tank failure within the 45-minute suppression threshold. This is actually the worst case scenario, and it represents only 2% of all the simulated wildfires.

Notably, six ignitions lie at the closest distance (see Figure 5), resulting in 2.5% of the total pool of wildfire simulations that would almost immediately threaten the facility. In the scenarios where fire reaches the facility before detection, response times can become negative (Fig. 6). Future work will implement constraints to avoid these undesired cases.

6. Conclusions

Optimally localized wireless sensor networks (WSNs), based on wildfire simulations, improve fire risk management by targeting specific performance metrics, objectives, and input data, including simulations and geospatial information. This study considers an early wildfire detection system that identifies fires and provides statistical insights into response times before the safety of critical infrastructure is compromised, including time-to-failure data.

The use of optimal sensor locations can significantly enhance the detection efficiency without increasing the number of sensors. The WSN optimization approach outlined in (Gómez-González et al., 2025) extends its utility beyond wildland protection, facilitating the development of applications to safeguard critical infrastructures and areas of significant economic, human, or ecological importance. Indeed, the WSN optimizer can easily be adapted to different situations and requirements by changing the objectives and constraints. The present study does not consider the presence of the critical infrastructure during the WSN optimization, and our analysis of response times is done for a WSN which is generally optimal. However, this can be addressed by integrating geospatial information relevant to the WII, either from public databases or site-specific computations. The setup of the case study can be further improved to avoid detecting fires after they have impacted the storage tanks. This would involve the introduction of constraints on the detection time to ensure detections occur only before any immediate threats to the facility. Considering that the work presented here provides a successful proof of concept, the above constitutes part of ongoing research.

Acknowledgement

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References

Blank, J. and K. Deb (2020). Pymoo: Multi-Objective Optimization in Python. *IEEE Access 8*, 89497–89509.

Dryad Networks GmbH (2024). How many sensors/mesh gateways/border gateways are needed to cover a forest? url: https://www.dryad.net/faq/how-many-sensors-mesh-gateways-border-gateways-are-needed-to-cover-a-forest (accessed: 03/03/2025).

European Parliament and Council of the European Union (2012, July). Directive 2012/18/EU of the European Parliament and of the Council of 4 July 2012 on the control of major-accident hazards involving dangerous substances, amending and subsequently repealing Council Directive 96/82/EC Text with EEA relevance.

Gómez-González, J. L., A. Cantizano, R. Caro-Carretero, and M. Castro (2024). Leveraging national forestry data repositories to advocate wildfire modeling towards simulation-driven risk assessment. *Ecological Indicators 158*, 111306.

Gómez-González, J. L., E. Marcoulaki, A. Cantizano, M. Konstantinidou, R. Caro, and M. Castro (2025). Simulated fire observables as indicators for optimizing wireless sensor networks in wildfire risk monitoring. *Ecological Indicators (accepted)*.

Khakzad, N. (2018). Impact of wildfires on Canada's oil sands facilities. *Natural Hazards and Earth System Sciences 18*(11), 3153–3166.

Khakzad, N. (2019). Modeling wildfire spread in wildland-industrial interfaces using dynamic Bayesian network. *Reliability Engineering & System Safety 189*, 165–176.

Landucci, G., G. Gubinelli, G. Antonioni, and V. Cozzani (2009). The assessment of the damage probability of storage tanks in domino events triggered by fire. *Accident Analysis & Prevention 41*(6), 1206–1215.

Mattioli, W., C. Ferrara, E. Lombardo, A. Barbati, L. Salvati, and A. Tomao (2022). Estimating wildfire suppression costs: a systematic review. *International Forestry Review 24*(1), 15–29.

Ministry for the Ecological Transition and the Demographic Challenge (MITECO) (2019). Los incendios forestales en españa, decenio 2006-2015 [Wildfires in Spain, decade 2006-2015].

Mohapatra, A. and T. Trinh (2022). Early Wildfire Detection Technologies in Practice—A Review. *Sustainability 14*(19), 12270.

Park, H., K. Nam, and H. Lim (2023). Is critical infrastructure safe from wildfires? A case study of wildland-industrial and -urban interface areas in South Korea. *International Journal of Disaster Risk Reduction 95*, 103849.

Partners in Protection (2003). *FireSmart: Protecting Your Community from Wildfire* (Second Edition ed.). Edmonton, Alberta, Canada: Partners in Protection. (url: https://firesmartcanada.ca/wp-content/uploads/2022/01/FireSmart-Protecting-Your-Community.pdf).

Planas, E., R. Paugam, A. Àgueda, P. Vacca, and E. Pastor (2023). Fires at the wildland-industrial interface. Is there an emerging problem? *Fire Safety Journal 141*, 103906.

Ricci, F., A. Misuri, G. E. Scarponi, V. Cozzani, and M. Demichela (2024). Vulnerability Assessment of Industrial Sites to Interface Fires and Wildfires. *Reliability Engineering & System Safety 243*, 109895.

Ricci, F., G. E. Scarponi, E. Pastor, E. Planas, and V. Cozzani (2021). Safety distances for storage tanks to prevent fire damage in Wildland-Industrial Interface. *Process Safety and Environmental Protection 147*, 693–702.

Schug, F., A. Bar-Massada, A. R. Carlson, H. Cox, T. J. Hawbaker, D. Helmers, P. Hostert, D. Kaim, N. K. Kasraee, S. Martinuzzi, M. H. Mockrin, K. A. Pfoch, and V. C. Radeloff (2023). The global wildland–urban interface. *Nature 621*(7977), 94–99.

Skretas, A., S. Gyftakis, and E. Marcoulaki (2022, August). A demonstration of sustainable pipeline routing optimization using detailed financial and environmental assessment. *Journal of Cleaner Production 362*, 132305.

Wu, Z., L. Hou, S. Wu, X. Wu, and F. Liu (2020). The time-to-failure assessment of large crude oil storage tank exposed to pool fire. *Fire Safety Journal 117*, 103192.