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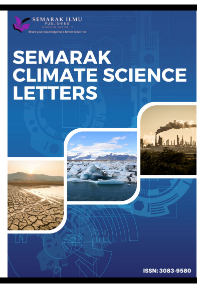

Climate Change Risk Assessment of Process Safety using Bayesian Network Model

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ABSTRACT

Climate change has introduced significant challenges to process safety in industrial operations, primarily due to the increasing severity and frequency of extreme weather events such as hurricanes, floods, and heatwaves. These evolving risks often exhibit complex interdependencies that exceed the capabilities of conventional risk assessment frameworks. This study addresses the need for a more robust approach by employing a Bayesian network model that integrates climate-related variables with traditional process safety elements. A comprehensive literature review was conducted to identify key climate parameters that influence industrial safety, which were then incorporated into the Bayesian framework to simulate diverse risk scenarios. The model was validated using two real-world case studies which is the Arkema plant explosion and incidents at the PrefChem facility. The model demonstrates how the methodology can capture climate-induced hazards and evaluate their impact on industrial processes. These simulations assess the probability of various risk outcomes under changing climate conditions. Based on these findings, targeted mitigation measures are proposed to enhance the resilience and safety of industrial operations in the face of climate variability. This research contributes to the development of a more comprehensive understanding of climate-driven risks and offers a practical decision-support tool for anticipating and managing their effects, thereby supporting safer and more sustainable industrial practices.

1. Introduction

Industrial process safety has traditionally focused on controlling internal operational hazards such as equipment failure, human error, and chemical reactivity. However, in recent decades, the external threat landscape has been reshaped by climate change, which now presents a formidable and dynamic risk factor. Changes in climate patterns have led to an increase in the frequency and intensity of extreme weather events including hurricanes, floods, lightning storms, droughts, and heatwaves.

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These events have the potential to disrupt industrial operations, damage safety systems, compromise infrastructure integrity, and escalate process-related accidents into catastrophic disasters. According to the Intergovernmental Panel on Climate Change (IPCC), climate extremes are expected to intensify in coming decades, which could significantly challenge the current paradigms of process safety and risk management [1].

The need to adapt industrial risk assessment frameworks to account for climate-related hazards has become increasingly evident in recent years. Notable incidents underscore this vulnerability. For instance, the explosion at the Arkema chemical plant in Crosby, Texas, following Hurricane Harvey in 2017, resulted from the loss of refrigeration power which led to the decomposition of organic peroxides [2]. Similarly, the fire at the Pengerang Integrated Complex (PIC) operated by PRefChem in Malaysia revealed gaps in emergency preparedness and exposed the sensitivity of safety systems to external stressors, including lightning and unanticipated shutdown sequences [3]. These events highlight the inadequacy of conventional static models that do not consider the probabilistic nature and compounding effects of environmental factors.

Traditional risk assessment methodologies such as Hazard and Operability Study (HAZOP), Failure Modes and Effects Analysis (FMEA), Fault Tree Analysis (FTA), and Bow Tie Analysis offer structured approaches for identifying and analyzing hazards. However, these methods are largely deterministic and do not inherently support dynamic risk updates or complex interdependencies between variables. They often assume stable operating conditions and do not incorporate external disruptions caused by climate variability. While some techniques have attempted to evolve by integrating layers of safety barriers and scenario-based analysis, they still lack the ability to quantify uncertainty and adapt in real time [4,5].

To address these limitations, probabilistic modelling tools have gained attention, particularly Bayesian Networks (BNs), which can represent cause-and-effect relationships using graphical structures combined with conditional probability tables. A Bayesian Network is a directed acyclic graph where nodes represent variables and edges denote causal relationships. This framework enables the integration of empirical data, expert judgment, and real-time monitoring to assess the likelihood of different events and their interdependencies [6,7]. Importantly, BNs support the updating of probabilities as new data becomes available, making them highly suitable for applications involving uncertain and evolving risk profiles.

Bayesian Networks have been successfully applied in various domains such as oil and gas safety [8], offshore platform operations [9], process control systems [10], and transportation risk management [11]. They have also been used in environmental risk modelling to assess the impact of climate change on ecological systems, water resources, and infrastructure reliability [12]. However, the application of BNs specifically for climate-related process safety remains limited. In many cases, climate parameters are either excluded or treated simplistically, failing to capture their dynamic interactions with technical systems and human factors.

Moreover, there is ongoing debate within the research community regarding the appropriate modelling depth and variable selection when integrating climate hazards into safety analysis. Some researchers argue for high-granularity models that simulate physical weather processes and their impacts on process units, while others advocate for more abstract models that prioritize usability and interpretability [13]. The selection of input data, the handling of uncertainty in climate projections, and the validation of the BN structure are also active areas of discussion [14].

This study aims to fill this critical gap by developing a comprehensive Bayesian Network-based risk assessment framework that incorporates climate-related variables and evaluates their influence on industrial process safety. The framework will simulate climate-driven risk scenarios such as loss of containment, thermal runaway, power outages, and flooding-induced equipment failure. It will be calibrated using historical incident data and expert elicitation, and it will be validated through two case studies: the Arkema explosion in the United States and the PRefChem fire in Malaysia. These case studies represent different industrial settings and climatic stressors, thereby providing a robust testing ground for the proposed model.

The main contributions of this work are threefold. First, it offers a novel approach for embedding climate uncertainty into process safety assessment using a probabilistic graphical model. Second, it enhances decision-making by providing dynamic risk estimates that can be updated in response to new data or forecasts. Third, it contributes to the resilience of industrial systems by supporting proactive risk mitigation and emergency preparedness strategies tailored to evolving climate risks.

In conclusion, the integration of climate variables into risk assessment using Bayesian Networks represents a significant step toward more adaptive, resilient, and forward-looking safety systems in the process industry. This work seeks to contribute to that vision by offering a structured, data-informed model that can guide policymakers, engineers, and safety practitioners in navigating the complex intersection between climate change and industrial risk.

2. Methodology

2.1 Project Workflow

The process began with data collection and incident analysis by using Centre for Chemical Process Safety (CCPS), Chemical Safety and Hazard Investigation Board (CSB) and reviewing existing articles or papers as the guidance, identifying relevant variables that contribute to climate change-related incidents. The Bayesian network model is then developed to represent the relationships between different variables and the probability of various outcomes. Through this model, various risk scenarios were simulated and then validated using the selected case studies which are Arkema Plant Explosion and Prefchem Incident. The final step was to get the findings into actionable strategies to enhance process safety. This is to ensure a resilient approach to industrial operations in the face of climate-related hazards. The project workflows are shown in Figure 1 below:

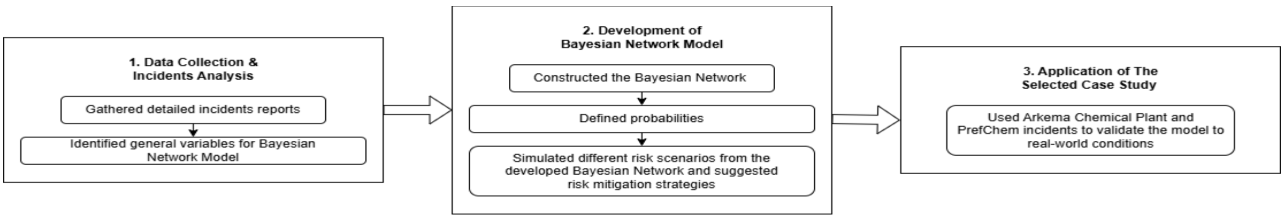

Fig. 1. Project workflow

2.2 Data Collection and Analysis

In the initial phase of this study, it was critical to systematically gather and analyse data related to the Arkema chemical plant explosions and PrefChem Incidents. The goal is to ensure a good understanding of the incident, focusing on the interaction between climate change and process safety failures.

2.2.1 Gathered detailed incident reports

- Source detailed reports and root cause analyses of the Arkema chemical plant explosions and PrefChem Incidents.
- Collected data from governmental agencies (e.g., Chemical Safety and Hazard

Investigation Board, Centre for Chemical Process Safety), company records, and credible news sources.

2.2.2 Identified general variables for Bayesian Network Model

- These variables should cover the factors contributing to climate change, its effects, and the hazards to process safety.

A. Factors Contributing to Climate Change:
   i. Greenhouse Gas Emissions: Levels of CO2, methane, and other greenhouse gases.
   ii. Deforestation: Rate of deforestation and loss of vegetation.
   iii. Industrial Activity: Extent of industrial emissions and waste.
   iv. Agricultural Practices: Use of fertilizers and livestock emissions.
   v. Energy Consumption: Reliance on fossil fuels versus renewable energy sources.

B. Climate Change Impacts:
   i. Temperature Increase: Changes in average temperatures and frequency of heatwaves.
   ii. Precipitation Patterns: Alterations in rainfall patterns, leading to floods or droughts.
   iii. Sea-Level Rise: Impact of rising sea levels on coastal infrastructure.
   iv. Extreme Weather Events: Frequency and severity of hurricanes, storms, and other extreme weather events.

C. Process Safety Elements:
   i. Infrastructure Integrity: Condition and resilience of industrial infrastructure.
   ii. Safety Measures: Existing safety protocols and measures.
   iii. Emergency Preparedness: Plans and resources for emergency response.

D. Risk Outcomes:
   i. System Failures: Likelihood of equipment or system failures due to climate impacts.
   ii. Chemical Spills: Probability of hazardous chemical releases.
   iii. Explosions and Fires: Risk of explosions or fires resulting from system failures.
   iv. Health and Environmental Impact: Potential health and environmental consequences.

2.3 Development of Bayesian Network Model

The next phase focused on developing a Bayesian Network model. This model would integrate the identified variables and their interdependencies to simulate risk scenarios and propose mitigation strategies.

2.3.1 Constructed the Bayesian Network

- Developed the network by defining nodes (representing variables) and arcs (representing dependencies).
- Used software tools like GeNIe Academic.

2.3.2 Defined Probabilities

- Assigned probability distributions to each node based on historical data, expert judgment, and incident report findings.
- This might involve quantitative data (e.g., frequency of extreme weather events) and qualitative assessments.

2.4 Risk Scenario Evaluation and Mitigation Strategies

After evaluating risk scenarios and understanding the potential impacts on process safety, the next crucial step was to develop and implement effective risk mitigation strategies.

2.4.1 Analysed Model Findings

- Analysed the simulation results to identify critical factors influencing process safety in the context of climate change.

2.4.2 Suggested Mitigation Strategies

- Proposed effective risk mitigation strategies, which might include infrastructure improvements, enhanced safety protocols, updated training programs, and investment in climate-resilient technologies.

2.5 Application of Case Studies to The Model

To assess and manage climate change and process safety risks, this study uses two case studies. The first is the Arkema Chemical Plant explosion, where reliance on cooling systems made the plant vulnerable to extreme weather. Hurricane Harvey caused severe flooding that disabled power and refrigeration, leading to chemical reactions and explosions. The failure of infrastructure, emergency systems, and lack of preparedness showed how industrial and environmental factors can interact across layers to cause major safety incidents. The second case is the PrefChem explosion at Pengerang. The plant’s high-pressure operations depended on stable equipment, which may have been stressed by rising temperatures [15]. These conditions, linked to climate change, weakened the pipeline, leading to rupture and explosion. Although safety systems were in place, there weren’t enough to prevent fatalities or injuries. Emergency teams responded quickly, but gaps in preparedness were evident. This case highlights how environmental stress and equipment failure can combine into serious accidents. Both incidents demonstrate how cascading failures which from environmental pressures to infrastructure breakdown and system failure can lead to disasters, emphasizing the importance of robust process safety and climate-resilient design.

3. Results

3.1 Interpretation of Developed General Bayesian Network

The general Bayesian Network model is illustrated in Figure 2, providing a graphical representation of the probabilistic relationships between key variables. Each node in the network represents a specific factor influencing process safety, such as climate hazards, technical failures, or human errors, while the directed edges indicate causal dependencies. This model serves as the foundational structure for simulating various risk scenarios by updating probabilities as new data or evidence becomes available.

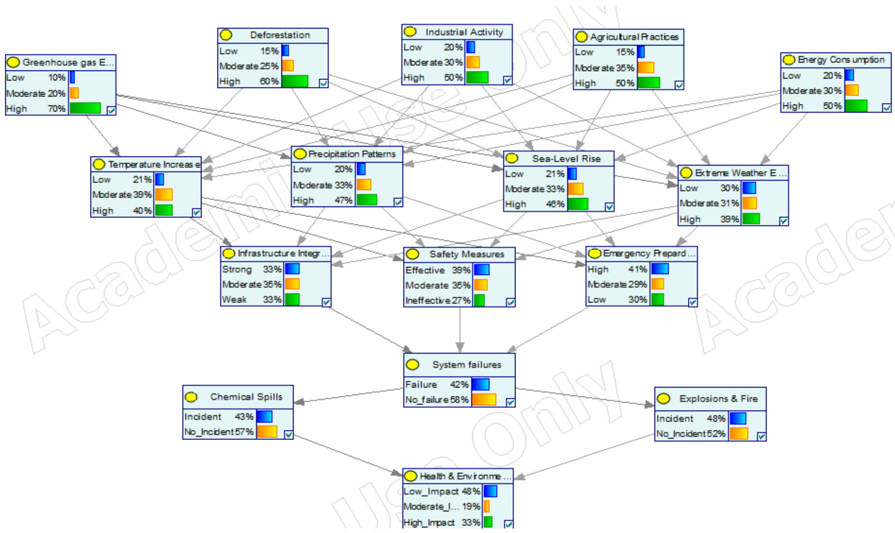

Fig. 2. General Bayesian Network Model (Bar View)

In this Bayesian Network model, each node represents a set of interconnected risks showing how climate change factors affect industrial safety. The structure and dependencies between nodes allow for a layered analysis, beginning with primary climate drivers and moving down through climate effects, infrastructure and safety system resilience, and finally, the risks of process failures and environmental impacts. This analysis explores the relationships in each layer of the model and their implications for process safety. Here, each layer will be gone through by explaining the connections and probabilities.

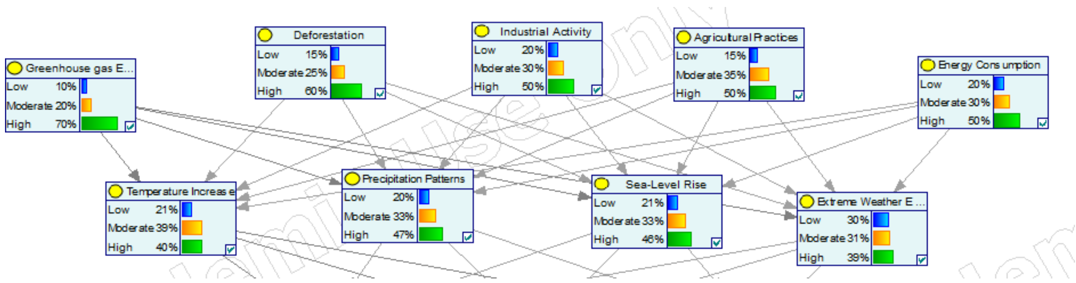

Fig. 3. Climate drivers and their impact on climate Eefects

In Figure 3, nodes like greenhouse gas emissions, deforestation, industrial activity, agricultural practices, and energy use are all part of the climate driver's layer. As the root causes, these nodes have a direct impact on climate effects like temperature increases, precipitation patterns, sea level rise, and extreme weather. According to this estimate, there is a 60% likelihood of deforestation and a 70% chance of significant greenhouse gas emissions. Precipitation patterns and temperature increases are greatly influenced by both causes.

This relationship aligns with studies that demonstrate how deforestation affects forests' ability to absorb carbon, increasing greenhouse gas emissions as well as increasing temperatures [16]. Furthermore, these climate effects are further pushed by high levels of industrial activity and energy consumption, each of which has a 50% chance of being high. This indicates that human activities collectively put more demand on climate stability.

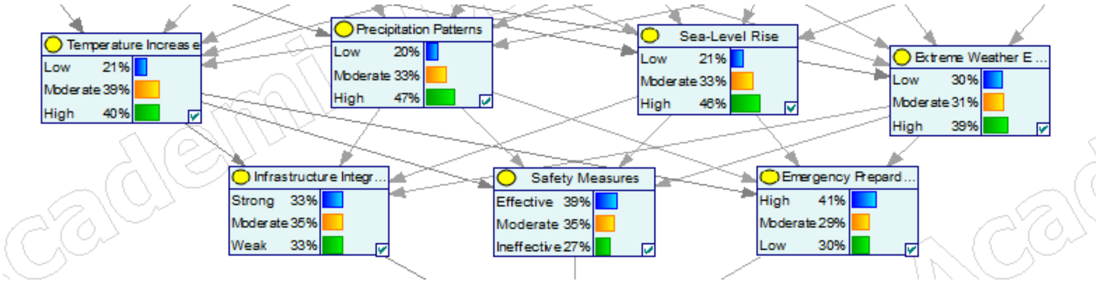

Fig. 4. Climate effects and their impact on infrastructure and safety

Sea level rise, precipitation patterns, increasing temperatures, and extreme weather events are all included in the climate change layer as shown in Figure 4. Safety measures and infrastructure integrity are under risk from these environmental changes. Sea-level rise, for example, has a 46% chance of being high while extreme weather events have a 39% chance of being high. A significant level of risk is indicated by the fact that 70% of Malaysia's critical facilities is in flood-prone locations. The risk of the integrity of infrastructure rises with rising sea levels and extreme weather events.

Equipment is also impacted by rising temperatures, particularly in sectors like chemical plants where machinery is sensitive to changes in temperature [17]. Infrastructure resilience is always being challenged by climate-related impacts, as evidenced by the model's equal distribution of infrastructure integrity across strong, moderate, and weak states (33% each). Infrastructure integrity is directly impacted by the probability of floods and storms brought on by extreme weather and sea level rise, which raises the possibility of chemical spills and system failures.

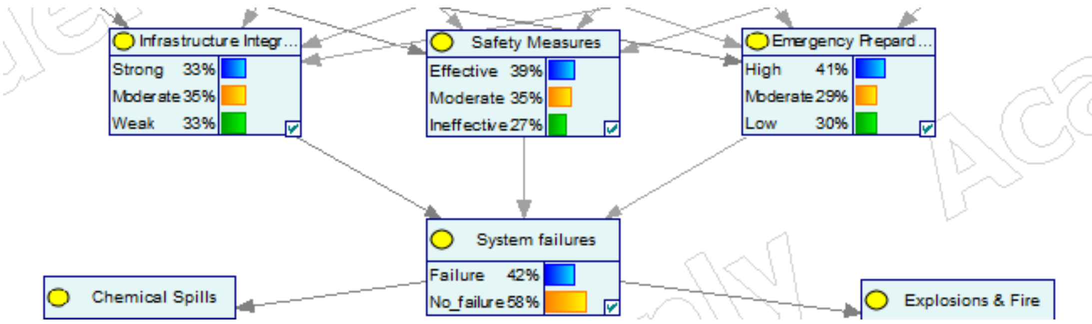

Fig. 5. Infrastructure, safety measures and emergency preparedness' impact on system failures

In Figure 5, the third layer includes infrastructure integrity, safety measures, and emergency preparedness. These factors are essential for industrial resilience. The model shows that safety measures are likely to be effective 39% of the time, but emergency preparedness has only a 41% probability of being strong. This highlights a vulnerability in response systems to extreme events. A lack of sufficient preparedness and strong safety systems increases the chances of system failures (42% probability of failure), especially when critical infrastructure is already under strain. This part of the model reflects real-world findings where outdated safety protocols and lack of adequate infrastructure adaptation have led to major incidents, particularly in flood-prone industrial zones.

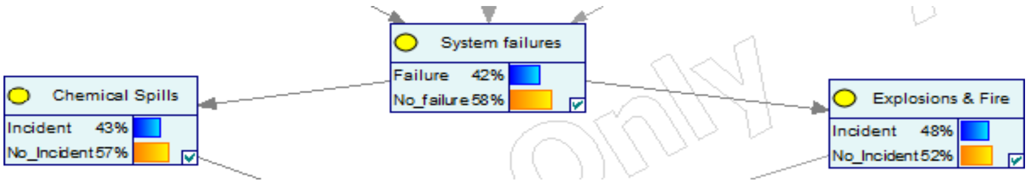

Fig. 6. Failures and their consequence on hazardous incidents

The node system failures act as a critical relationship of infrastructure and safety weaknesses, resulting in chemical spills (43% incident probability) and explosions or fires (48% incident probability) as shown in Figure 6. This connection demonstrates how dangerous events might arise from weaknesses in the system brought on by climate change. Research confirms that environmental factors, such as flooding or extreme temperatures, increase the risks of chemical spills and fires in industrial settings [18].

The model demonstrates that when system failures are likely, the chances of hazardous events, like spills, rise significantly. This suggests that the network effectively captures the relationship between climate-driven infrastructure failures and safety incidents, highlighting a need for stronger, climate-adapted safety and infrastructure measures.

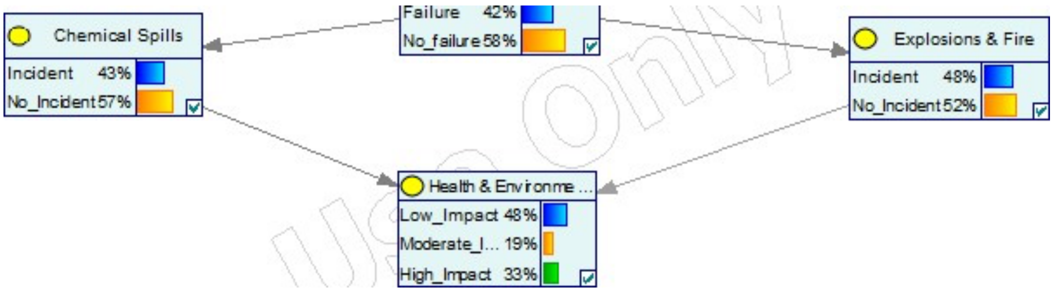

Fig. 7. Health and environmental effects of incidents

In Figure 7, the health and environmental effects node captures the impact of chemical spills, explosions, or fires on public health and the environment. With a 33% chance of severe impacts, the model implies that industrial incidents under climate pressure can lead to lasting health issues and environmental harm. In regions where industrial operations are exposed to extreme weather, chemical spills contribute to respiratory illnesses and environmental contamination [19].

The connection between hazardous incidents and health impacts shows how flaws at every stage create a cumulative risk, as climate-related risks in safety and infrastructure systems spread to impact ecosystems and public health. Better pollution control, risk management, and industrial resilience methods are desperately needed in Malaysia to shield communities from the effects of climate-driven industrial hazards, as evidenced by the model's high likelihood of serious health effects.

3.2 Arkema Chemical Plant Explosion

The Hurricane Harvey-related Arkema chemical plant incident in Crosby, Texas, gives an actual example of how serious industrial catastrophes can result from weak infrastructure, poor safety protocols, and inadequate emergency planning [20]. To determine if similar events could reliably result in comparable accidents, this analysis compares Arkema's actual risk factors and outcomes with simulated probability using a Bayesian network model. Table 1 shows the nodes that contributed to the Arkema incidents, and the evidence (states) are then applied to the model to see the risk outcome on the incidents while Figure 8 shows that the evidence is set in the model:

Table 1
Nodes with assigned states for Arkema incidents

Node	State	Rationale
Greenhouse Gas Emissions	Low	Arkema's direct impact on emissions is not a primary factor in this incident.
Industrial Activity	Moderate	Arkema's industrial activities involve chemical storage, impacting its safety needs.
Agricultural Practices	Low	Agriculture is unrelated to Arkema's operations or the incident.
Energy Consumption	Low	The incident wasn't driven by energy consumption patterns but rather by process safety issues.
Extreme Weather Events	High	Flooding from Hurricane Harvey is a primary driver in the incident.
Infrastructure Integrity	Weak	The plant's systems failed due to infrastructure vulnerabilities under flood conditions.
Safety Measures	Moderate	Safety protocols existed but were not strong enough for severe flooding.
Emergency Preparedness	Moderate	The emergency response was insufficient for the scale of the disaster.

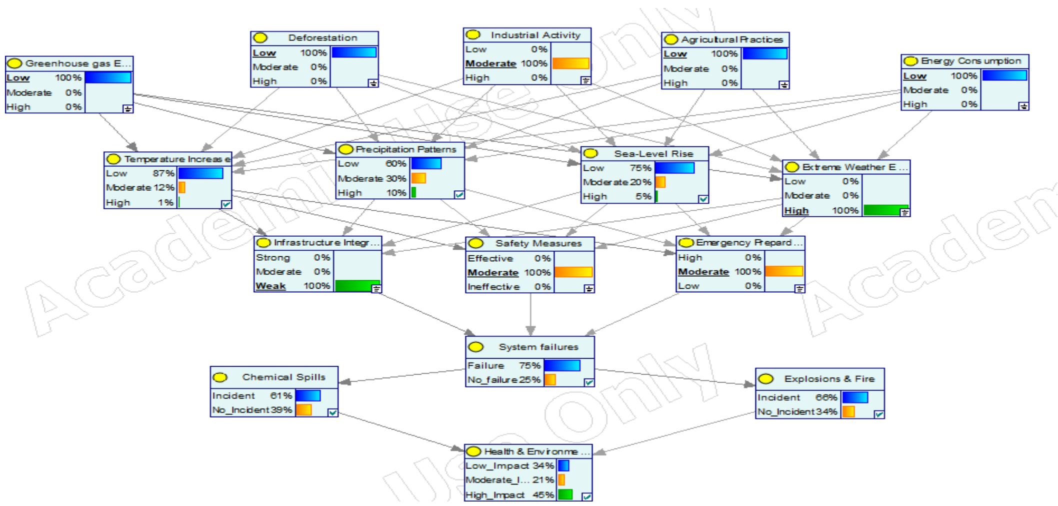

Fig. 8. Arkema case study results

Hurricane Harvey's unprecedented flooding sparked the Arkema disaster and was a primary cause of the plant's critical infrastructure breakdown. The network accurately reflects the risk posed by severe floods since Extreme Weather Events are set to "High" (100%) in the model. In this instance, extreme weather directly led to a 75% chance of system failure, which underscores the sensitivity of industrial facilities to natural disasters. Arkema and other facilities should think about placing critical infrastructure above possible flood levels and making investments in advanced flood-proofing techniques as a way of mitigating future flooding.

Arkema has safety procedures in place, but they were not enough to stop the disaster's scale. This insufficiency is reflected in the model, which displays a 100% chance that safety measures will fail at the "Moderate" level. This is consistent with the actual result, in which containment measures and backup generators were overloaded. Improving safety measures to foresee extreme situations is crucial, as a lesson learnt. Response capabilities would be improved, for example, by the installation of advanced monitoring systems that might offer real-time data on rising water levels and start early shutdowns or relocations.

Given the intensity of Hurricane Harvey, the emergency response from the Arkema complex was inadequate. When Emergency Preparedness is set to "Moderate" in the model, there is still a 75% chance of system failures and a high probability of events (explosions at 66% and chemical spills at 61%). These probabilities reflect the real situation, in which flooding and the fires that followed raised serious issues for the environment and public health. Facilities should think about strong emergency response procedures, such as automatic shutdowns, community evacuation plans, and chemical-neutralizing fire prevention techniques, to increase preparedness [21].

When chemicals ignited at Arkema, poisonous vapors were released, posing serious health hazards and having a negative impact on the environment. Under similar conditions, the model accurately represents the Arkema instance and predicts a 45% risk of a high impact on the environment and human health. Improved containment of hazardous items, particularly volatile compounds, could be one of the enhanced mitigation techniques. For instance, establishments can put in place fire suppression systems and secondary containment units that will start up automatically in the event of a power outage or other environmental stressors.

3.3 Risk Mitigation Strategies

The Arkema tragedy highlights how crucial proper risk management plans are for high-risk companies, especially those located in regions exposed to severe weather. The following mitigation strategies are recommended based on the model's results and the real case:

i. **Enhanced Flood Resilience and Infrastructure Design:** Arkema and similar facilities should make investments in flood-resistant designs because of the significant danger of infrastructure failure, as the model illustrates. To reduce heat-induced chemical decomposition, precautions should be taken by waterproofing backup power supplies, raising important electrical systems, and creating storage units with temperature-resistant construction [22].

ii. **Upgraded Safety Protocols and Monitoring Systems:** Arkema's emergency response failure is consistent with the model's prediction of ineffective safety measures. Risk could be decreased by putting in place redundant safety measures like thermal insulation for volatile chemicals and backup generators in high places. Additionally, during extreme weather events, advanced monitoring technologies may offer early warnings for infrastructure risks.

3.4 The PrefChem Explosion and Fire at the Pengerang Integrated Complex

The PRefChem explosion at the Pengerang Integrated Complex in Johor, Malaysia, provides a good example of how critical industrial failures can arise from vulnerabilities in infrastructure, operational safety, and emergency preparedness. To explore whether similar conditions could lead to comparable incidents, this analysis applies a Bayesian network model to evaluate the contributing factors and their cascading effects. Table 2 identifies the nodes relevant to the PRefChem incident, along with their assigned states, which are based on evidence from the case. These states are then input into the model to simulate the potential outcomes and assess the risks associated with such incidents.

Table 2
Nodes with assigned states for PrefChem incidents

Node	State	Rationale
Greenhouse Gas Emissions	Low	The PRefChem incident was not directly driven by emissions or related environmental contributions.
Deforestation	Low	Deforestation is unrelated to the plant's operations or the incident.
Industrial Activity	High	The plant's high-pressure petrochemical processes created significant operational risks.
Agricultural Practices	Low	Agriculture is not connected to the industrial activity or risks of the PRefChem facility.
Energy Consumption	Moderate	Energy use is high due to complex operations, though it was not a direct cause of the incident.
Temperature Increases	Moderate	Rising ambient temperatures likely stressed equipment, contributing indirectly to the pipeline rupture.
Extreme Weather Events	Low	No significant weather events (flooding, storms) occurred during the incident
Infrastructure Integrity	Weak	The pipeline failure highlights vulnerabilities in maintenance or design, contributing to the explosion.

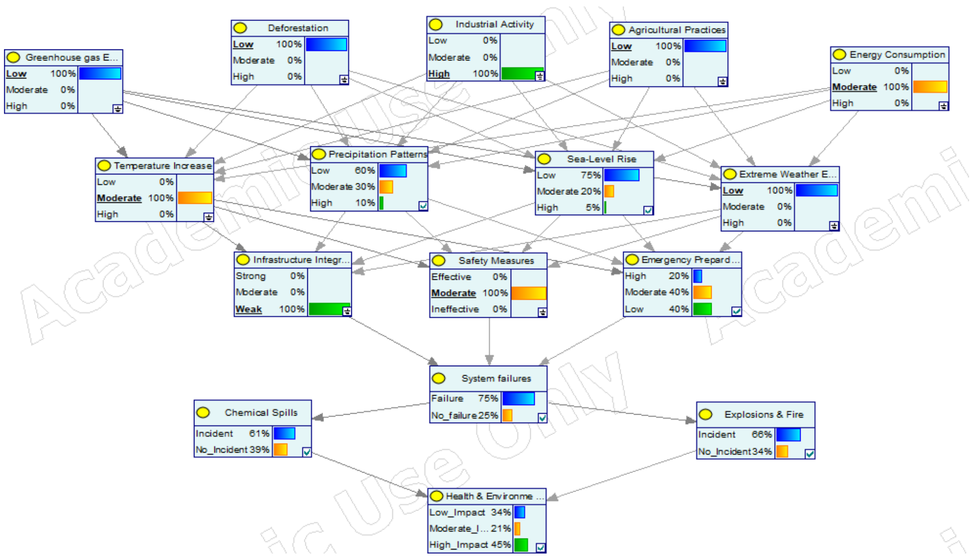

Fig. 9. PrefChem case study results

The PRefChem incident analysis, based on the Bayesian Network model and the evidence set as shown in Figure 9, reveals several key findings regarding the underlying causes and consequences of the explosion. The extreme weather events were rated as a low risk factor (100% low), indicating that severe weather did not contribute significantly to the incident, unlike the Arkema disaster where flooding was a primary cause. Instead, the PRefChem incident stemmed more from internal operational risks, particularly in the industrial activity at the plant, which was assessed as a high risk (100%). The high-pressure petrochemical processes created substantial operational hazards, contributing directly to the failure.

Regarding infrastructure integrity, the model assigns it a weak rating (100% weak), which suggests that vulnerabilities in the plant's design or maintenance played a crucial role in the explosion. This aligns with the observed failure of critical systems, such as the pipeline rupture, which points to inadequate infrastructure that could not withstand the operational stresses. The safety measures were rated as moderate (100% moderate), indicating that while some safety protocols existed, they were insufficient to prevent or mitigate the severity of the explosion. The lack of robust safety measures highlights the need for more advanced safety systems and better preparedness for such operational risks.

In terms of emergency preparedness, the model similarly indicates a moderate risk (100% moderate), which corresponds to the insufficient response capacity observed during the incident. Despite emergency protocols, the plant faced significant failures, as reflected in the 75% chance of system failure in the model, with high probabilities of chemical spills (61%) and explosions (66%). This underlines the need for stronger emergency response systems, such as automated shutdown mechanisms and more effective evacuation plans, to reduce the impact of such failures.

Finally, the health and environmental impact of the incident was also predicted to be significant, with a 45% chance of high impact on health and the environment, emphasizing the dangerous consequences of industrial accidents. This prediction is in line with the actual situation, where the explosion led to the release of hazardous chemicals, which caused serious health and environmental damage. The five fatalities were largely due to toxic exposure and the subsequent fires.

4. Conclusion

This study successfully developed a Bayesian Network model to assess the impact of climate change on industrial process safety, addressing critical gaps in traditional risk assessments by incorporating climate related variables and system interdependencies. The model demonstrated that strong emergency preparedness and climate resilient infrastructure significantly reduce risk, as shown through simulated scenarios and validated by real world incidents at the Arkema and PrefChem plants. The findings highlight the need for industries to adopt adaptive safety measures and infrastructure capable of withstanding extreme weather events. Although certain enhancements such as expert input for probability values, inclusion of more climate variables, broader case studies, and integration of machine learning were not implemented due to time and resource constraints, they are valuable recommendations for future research to strengthen the model's accuracy and flexibility. Overall, this work contributes a useful framework for integrating climate risks into process safety planning, supporting more resilient and sustainable industrial operations.

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